A MODEL FOR PERFORMANCE EVALUATION OF CLIMATE-ADAPTIVE BUILDING ENVELOPES USING PARAMETRIC MODELS AND MULTI-CRITERIA OPTIMIZATION

A Dissertation

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ABSTRACT

The goal of this research is to enable designers to evaluate the performance of Climate-Adaptive Building Envelopes (CABE) to make better decisions at the conceptual design stage. This goal was accomplished by delivering three contributions to the fields of parametric modeling, building performance simulation, and multi-criteria optimization. There are three main challenges in CABE performance evaluation that cannot be overcome by conventional methods: 1) defining a suitable relationship between environmental factors and their thresholds by focusing on a given condition in CABE behavior control; 2) representing a CABE's time-series behavior by using a single Building Performance Simulation (BPS) model; and 3) managing information related to a CABE's performance and behavior for use in design decisions. To overcome these issues, this research developed a new CABE performance evaluation method called Parametric Behavior Maps (PBM), which makes three key contributions. First, the PBM method is able to generate a CABE operation schedule as an Hourly Behavior of Openness (HBOO) scenario to evaluate CABE performance using a single BPS model. Second, the PBM method produces more reliable outcomes than the conventional process, especially in terms of the time-lag effect of thermal performance. Third, the use of a Function-based Behavior Control System (FBCS) for the CABE efficiently facilitates a multi-criteria optimization process by progressively simulating alternative HBOO scenarios, allowing designers to choose the best scheme. These three

contributions offer logical proof that the use of parametric modeling and simulation tools can help designers make better decisions regarding CABE alternatives.

The PBM method was validated by investigating several test cases. First, static shading scenarios were developed using the PBM; the amount of incoming solar radiation was then compared with outcomes from the BPS with static shading. Second, indoor temperature profiles were simulated using the PBM method and an HBOO scenario; the results were compared with the outcomes obtained from the existing method, in order to determine the PBM's reliability. Third, the integration of the PBM method and evolutionary multi-objective optimization technique illustrates the usefulness of the FBCS in CABE performance optimization.

DEDICATION

I would like to dedicate my dissertation to my devoted family, in gratitude for their love, commitment, and support.

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NOMENCLATURE

ABE	Adaptive Building Envelopes
ASE	Annual Sunlight Exposure
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
BIM	Building Information Modeling
BPS	Building Performance Simulation
BREEAM	Building Research Establishment Environmental Assessment Method
CABE	Climate Adaptive Building Envelope
CAD	Computer-Aided Design
DA	Daylight Autonomy
DF	Daylighting Factor
DGI	Daylighting Glare Index
DGP	Daylighting Glare Probability
DOE	U.S. Department of Energy
EMO	Evolutionary Multi-objective Optimization
ERC	Externally Reflected Component
GHI	Global Horizontal Irradiation
HBOO	Hourly Behavior of Openness
HSA	Horizontal Shadow Angle

HVAC	Heating, Ventilation, and Air Conditioning
IEQ	Indoor Environmental Quality
IESNA	Illuminating Engineering Society of North America
IRC	Internally Reflected Component
LEED	Leadership in Energy and Environmental Design
MOO	Multi-Objective Optimization
MOOP	Multi-Objective Optimization Problems
MSSB	Multiple Simulations with Static Behavior
NSRDB	National Solar Radiation Database
PBM	Parametric Behavior Maps
PMV	Predicted Mean Vote
PPD	Predicted Percent Dissatisfied
SC	Sky Component
sDA	Spatial Daylighting Autonomy
SHGC	Solar Heat Gain Coefficient
SST	Schedule of Solar Transmittance
TMY	Typical Meteorological Year
U	Heat Transfer Coefficient
UDI	Useful Daylighting Illuminance
VDF	Vertical Daylighting Factor
VSA	Vertical Shadow Angle
VSC	Vertical Sky Component

WWR	Window-to-Wall Ratio

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CHAPTER I

INTRODUCTION

1.1. Overview

Research into building with Climate Adaptive Building Envelopes (CABE) technology is an effort to respond not only to changing environmental conditions, but also to the various aesthetic needs of design (Linn and Fortmeyer, 2014). A CABE is a building envelope that changes in geometry or material characteristics in response to weather stimuli; the goal is to achieve higher levels of performance, typically in terms of energy efficiency or daylighting effectiveness. Currently, the development of building design and performance analysis platforms have led to rapid changes in the building design process (Clayton et al., 2010). However, current performance-driven building design methodologies provide only limited support for performance evaluations, and ultimately are unable to provide data for design decisions that are needed to produce effective CABE alternatives (Loonen et al., 2017).

This research addresses the following primary research question: Can an improved process be devised by integrating parametric design into simulation tools to support CABE performance evaluations to aid in selecting among alternatives during the conceptual design phase? This primary question relies on separate, secondary questions that can be answered independently:

(1) Can parametric modeling be used to model a CABE to incorporate variation of geometric states across time?

(2) Can a parametric model and its multiple geometric CABE states be analyzed using multi-criteria performance simulations?

(3) Can multi-criteria simulation results be subjected to multi-objective optimization to support decisions on CABE alternatives during the early stages of design?

To answer these questions, this research devised a new method that extends the performance evaluation process to include the time series operation scenarios of CABE. The method integrates the computer technology of parametric design in order to represent a CABE model with performance simulations and optimization tools. Tests were conducted to determine the extent of the search space accommodated by this method allowing for the exploration of the CABE design, as well as facilitating analysis and implementation.

This study relied upon three main aspects of Computer-Aided Design (CAD) research, including: 1) parametric modeling, 2) performance-driven building design methodology, and 3) multi-criteria optimization. First, the representation of time series variables using parametric modeling facilitates the production of CABE models that correspond to variations in geometric states across time. Second, the development of a performance evaluation methodology for CABE enables designers to evaluate the performances of their alternatives during the conceptual design phase. Third, the method produces better information on the impact of a CABE's operation scenarios according to multiple performance criteria, thus enabling more informed design decisions.

To develop this method, the following research phases were conducted:

(1) Elaboration of the research agenda addressing performance-driven CABE design by reviewing the literature on and existing practices for CABE creation;
(2) Development of a performance evaluation algorithm for CABE technology by integrating parametric modeling and simulation;
(3) Validation of the new algorithm with comparative studies; and
(4) Implementation of a multi-criteria optimization framework to support decisions related to CABE design with an optimum control strategy.

This chapter provides an overview of this research, including the background, research problem, and objective. It also describes the contributions made by this research. An outline of each subsequent chapter is also provided in the final section.

1.2. Background

This section briefly introduces the background of this research, including the motivation for its completion, state of the art, and future applications of CABE design. The integration of building design and CABE technology was achieved through an interdisciplinary study of parametric design, building performance simulation, optimization, fabrication with advanced materials, and operation management.

1.2.1. Motivation

CABE systems have widely been used in building envelope design and research as a means of enhancing the sustainability of the built environment (Loonen et al., 2013).

This section briefly introduces certain motivations for using CABE systems, including their characteristics, benefits, and overall significance.

1.2.1.1. Existing Adaptive Building Envelopes

Adaptive Building Envelopes (ABE) have the ability to effectively adapt to changes in their environment (Schmidt III et al., 2010). In the last few decades, the development of the Architecture, Engineering, Construction, and Owner-operated (AECO) industry has facilitated the design and construction of ABEs, which can be categorized into two objectives. First, existing buildings have been integrated with CABEs in order to respond to environmental factors such as view, daylight, temperature, and wind (Loonen, 2010). Second, ABEs have been considered representative of both natural and social phenomena, focusing on aesthetic, community, and educational objectives (Mignonneau and Sommerer, 2008). Although ABEs can play a key role in increasing sustainability and representing phenomena from their responses to changes in the environment, there are simultaneous critical risks related to the increase in payback time stemming from the high cost of investment, maintenance, and failure (Loonen et al., 2013).

1.2.1.2. Characteristics of CABEs

The main CABE characteristics can be divided into three categories: geometric transformation, materials, and behavior. First, CABEs' geometric transformations combine translation, rotation, scaling, and materials deformation to create folding, sliding, expanding, creasing, hinging, rolling, inflating, fanning, rotating, and curling motions (Loonen et al., 2013; Moloney, 2011). Second, CABEs use material properties to manipulate their thermal elements, color, and level of transparency (Addington and Schodek, 2005). For example, a photo-sensitive glass may darken when exposed to bright light. Third, CABEs respond to environmental input such as solar radiation, temperature, humidity, and wind, implying that specific operational schedules (behaviors) or sensors and triggers are necessary to control their time-based motions (Tzempelikos and Shen, 2013). To this extent, CABE behaviors can be defined as time series variations of geometric transformations and material properties. In this research, the term Hourly Behavior of Openness (HBOO) is used to describe the hourly degree of openness of a CABE's geometric design parameters over time, as an hourly operation schedule.

1.2.1.3. Need for CABEs

There are several benefits associated with CABEs, such as environmental protection, increases in human comfort, and aesthetics. First, buildings with CABEs perform better than conventional buildings by reducing energy consumption and providing occupants with high levels of thermal and visual indoor quality (Tzempelikos and Shen, 2013). Second, although high-quality indoor spaces are not directly associated with cost value, they increase human productivity and health by responding to changes in the environment and human demand (Zuo and Zhao, 2014). Finally, CABE elements offer aesthetically interesting features and a unique design identity by interacting with human behavior, the environment, and the area's historical context (Al-Kodmany, 2014).

1.2.1.4. Sensitivity of Building Components

There are various passive solar design strategies associated with building components, such as building form, orientation, window-to-wall ratio, glazing type, shading, and the thermal properties of the walls and roof (Stevanović, 2013). Due to uncertainties associated with local climate and the wide variety of possible building components, the implementation of these strategies is not straightforward, especially in highly dense urban environments. It is important to identify the most significant building components at the specific location if one is to create effective design alternatives (Yıldız and Arsan, 2011). For example, the most important building parameter that affects cooling and heating loads in hot-humid climates is windows; however, decisions regarding windows depend upon the window-to-wall ratio, heat transfer coefficient (U) value, and Solar Heat Gain Coefficient (SHGC) (Yıldız and Arsan, 2011).

For five cities in different climatic zones in Italy, the envelope's transparent surface ratio is the most significant factor for heating and cooling loads (Mechri et al., 2010). In this case, fenestrations are an essential building design element in terms of aesthetics, and their integration with passive solar design strategies can play a significant role in reducing energy consumption (Stevanović, 2013). Thus, the use of a suitable shading device at a location where it can perform efficiently serves to block direct solar radiation through the fenestration area (Bellia et al., 2013). To this extent a CABE, as an example of a suitable shading device, could play a significant role in reducing energy consumption and creating comfortable indoor environments.

1.2.2. State-of-the-Art CABE Technologies

Advances in computational methods are providing better ways of conceiving of CABE buildings and predicting their performance, even as new technologies in mechanical and materials engineering are providing previously unrealizable methods of production. Computational methods of particular relevance include parametric and performance-driven building design. Of particular note with regards to methods for producing adaptable buildings is the advent of smart materials.

1.2.2.1. Parametric Design

Parametric design allows designers to define specific relationships among the various design variables and constraints, which leads to automatic changes and updated alternatives with few parameters (Jabi, 2013). Parametric design techniques are widely utilized at all scale ranges, from interior to urban design (Schumacher, 2009). In addition, the use of Building Information Modeling (BIM) technology and parametric design methods are coupled with various analytical tools throughout the building design and construction process (Wong and Zhou, 2015). Lately, the development of visual programming interfaces has enabled users to generate dynamic forms without the traditional paradigm of programming and scripting, and facilitated easy integration with other plug-ins for simulation, optimization, and visualization (Yi and Kim, 2015).

Consequently, this has provided students and researchers with digitized methods for use in understanding and experimenting with kinetic objects, and collaborating with experts in other fields such as robotics and materials science. This trend will continue to lead advanced CAD technology and the industry.

1.2.2.2. Performance-Driven Building Design

Performance-driven building design is the process of forming and generating designs of a desired level of performance by integrating analytical simulation techniques (Oxman, 2006). The availability of advanced technologies in CAD and performance evaluation tools has led to a paradigm-shift in the design process (Kolarevic and Malkawi, 2005). These tools have enabled the use of optimization processes at the early design stages; these processes incorporate various decision variables related to building form and design objectives that support sustainable development, integrated design processes, and decision making (Machairas et al., 2014).

Although advanced technology plays an important role in supporting performance-driven decisions in the early design stages, it cannot guarantee that a passive building design strategy is necessarily the best, because there are: (1) immeasurable design variables such as the building's form, orientation, width, length, height, and shading; (2) various site-specific urban contexts and local climate considerations; (3) a lack of integration among different tools; (4) different characteristics related to performance objectives, such as energy, daylighting, and natural ventilation; and (5) limitations related to optimization algorithms and their ability to address variations (Konis et al., 2016). Accordingly, sequential performance-driven building design phases ranging from site analysis and building design to performance analysis and optimization have been developed to create high-performance buildings; each phase contains several sub-phases that are supported by advanced technologies. For example, the building design phase includes sequential sub-phases such as massing, floorplan layout, windows, and shading design (Konis et al., 2016).

1.2.3. Future CABE Technology

Most existing CABE practices respond to environmental changes by relying on mechanical equipment and structures with additional energy sources (Menges and Reichert, 2012). The current CABE technology responds to input data about the environment by following a four-step process: sensing, computer processing, actuating, and shape changing (Fox and Yeh, 2000). Recently, new and more advanced smart materials have emerged as self-regulating envelope systems. In other words, the application of smart materials enables buildings to respond to external stimuli via self-sensing, self-actuating, and self-shape-changing without the need for additional energy sources; together, these steps merge into one integrated process (Bogue, 2014). Several researchers have investigated the possibility of using certain smart materials in architecture, such as shape memory alloy and pine cone material, as a response to solar heat gain and relative humidity (Payne and Johnson, 2013; Reichert et al., 2015). Although only a few pavilions have been developed with smart materials, more applications for larger buildings will be investigated and are likely to provide unique approaches to building design.

1.3. Research Problem

Designs employing CABE technology are often motivated by the intention to achieve energy savings and increase the level of comfort in an indoor environment. However, much of the research in this area has merely described how to create physical geometric motion, and has not included performance evaluations or management of alternatives. This is due to limitations in the current performance-driven CABE design methodology related to: (1) inadequate simulation methods, (2) the inability to apply simulations at the early stages of design and manage the resulting information about alternatives, and (3) poor tools for studying the optimization of solutions across multiple criteria (Loonen et al., 2017). This research addresses these three impediments to the widespread adoption of CABE technology.

1.3.1. Limitations to the Simulation Method

Unlike static buildings and envelopes, performance analyses of adaptive buildings must consider seasonal, monthly, daily, and hourly variations in a building's geometry, materials, and behavior. Although some researchers have addressed these issues, their models often tend to include venetian blinds and screens as the only moveable envelope features incorporated into their energy and daylighting performance analyses (Manzan and Padovan, 2015). In other words, current simulation tools do not allow users to update three-dimensional complex geometry as moveable shading and then simulate its effects with hourly behavior. Consequently, current methods cannot support performance-driven CABE design (Kim et al., 2015).

1.3.2. Lack of Integration of Performance into CABE Designs

Although decisions at the conceptual design stage are often the most influential in determining building performance, many times the design decisions at that stage focus largely on aesthetic variables (Wang et al., 2006); later design stages allow for only limited attention to be paid to performance improvement (Wang et al., 2006). As clients demand higher levels of building performance, architects are increasingly held responsible for delivering well-informed design decisions. Since current simulation methods do not produce data about integrated CABE performance, designers and engineers are precluded from considering CABE design options that have the potential to improve performance (Kasinalis et al., 2014). Information on building performance in the early stages of a project could lead to an increase in the use of CABE design methods and, ultimately, higher-performance buildings.

1.3.3. Limited Optimization Strategies

The choice of a design solution among alternatives inevitably requires trade-offs in optimization criteria. Although optimization algorithms' efficiency in problem solving depends upon the capacity of the algorithm and the complexity of the problem, well-defined design variables, constraints, and objectives are directly related to successful optimization processes, results, and computational costs. Especially of note, a large number of variables tends to cause optimization failures and inform users of inaccurate solutions (Nguyen et al., 2014). To overcome this problem, some researchers have introduced methods of controlling multiple individual variables using only a few agent variables (Yi and Malkawi, 2009). However, with CABE systems, the hourly time series variations in geometry compel a significant increase in the number of variables, meaning that optimization processes cannot be easily integrated into CABE design. Development of a framework for optimizing among multiple criteria could help designers manage the complexity of CABE solutions.

1.4. Research Objective and Hypotheses

1.4.1. Research Objective

The goal of this research was to produce an algorithm that employs conventional simulation software for energy performance and daylighting as a means of enabling designers to choose high-performing CABE designs from among the various alternatives. To achieve this goal, an algorithm was developed that represents the CABE model, evaluates its performance, and generates optimum HBOO information with multi-criteria optimization; this algorithm was implemented in parametric design environments to integrate CABE performance at the conceptual design stage.

The overall workflow of a plausible CABE design method can be described as follows:

(1) Development of an algorithm for representing CABE models, including HBOO scenarios;

(2) Development of an algorithm for simulating the environmental performance of CABE designs, considering both energy and daylighting; and

(3) Situation of the results within a multi-criteria optimization framework to support alternative decisions and future implementation.

As described above, a challenge in simulating CABE design alternatives as compared to static building envelopes is that CABE simulations must include time series variations of geometric transformations and material properties. This research focused on how HBOO scenarios could be integrated into CABE simulations and multi-criteria optimization in a parametric modeling environment.

1.4.2. Limits to the Research Scope

The research scope can be summarized based on CABE technology's main characteristics: geometric transformation, materials, and behavior. First, this research did not address the issue of geometric variations in CABE design. In other words, pre-designed CABE alternatives were used to conduct the test cases. Second, consideration of a CABE's material property changes were not included. Third, although CABE behavior involves time-series motion variables such as speed, acceleration, delay, and patterns (Parkes, 2009), HBOO values were generated at equal intervals regardless of motion variables, once an hour. Fourth, consideration of reliability, maintenance, and installation costs were outside the scope of this research. Finally, this research did not address ABEs associated with aesthetic, social, and educational objectives.

1.4.3. Hypotheses

This research primarily hypothesized that designers could make better decisions related to CABE alternatives by using parametric modeling and simulation tools. The sub-hypotheses that support this primary hypothesis and drive this research are as follows:

(1) Parametric design can represent a CABE and its time series variations in geometry in a manner sufficient to support performance simulation and assessment.

(2) Performance simulation tools can perform simulations of each geometric state and manage the aggregate performance.

(3) Multi-objective optimization can help architects evaluate CABE alternatives.

1.5. Research Strategy

This section introduces the overall research strategy used to obtain evidence and ultimately validate the hypotheses employed in this research.

1.5.1. Methods

The validation of building performance simulation algorithms is a critical aspect of the development process. There are three common methods used in validating simulation algorithms: comparative studies, analytical verification, and empirical validation (Shrestha and Maxwell, 2006).

1.5.1.1. Comparative studies

A comparative study is when two building energy models with the same input parameters are directly compared, using measured data from real buildings (Judkoff et al., 2008). In other words, this method simulates a single energy model using an existing validated instrument and a newly developed algorithm, and then compares the results. For example, in the early stages of one building's design, a simple tool was developed to evaluate energy demand; it was validated by comparing its results with those obtained from BSim, a detailed building simulation tool developed by Danish Building and Urban Research (Nielsen, 2005). Although the main weakness of this method is the absence of a standard truth model, there are several important benefits: (1) less input uncertainty, (2) low cost, and (3) a large number of possible test comparisons (Judkoff et al., 2008).

1.5.1.2. Analytical verification

The analytical verification method compares simulation results from simple test cases with calculation results obtained from analytical solutions, such as fundamental heat transfer mechanisms (Shrestha and Maxwell, 2006). Although the test cases cannot represent real buildings, the main strength of this method is the use of a truth model that can eliminate uncertainty. However, this is also its primary weakness, due to: (1) the limited number of cases from which analytical solutions can be derived, and (2) its inadequacy when testing real buildings (Judkoff et al., 2008).

1.5.1.3. Empirical validation

In the empirical validation method, data from a real building or test cell is utilized as a standard truth model and compared to the results produced by simulation tools (Judkoff et al., 2008). This method requires an excessively large amount of measured data to increase the level of validation (McKinstry et al., 1980). The validation process evaluates how accurate the energy simulation results are by how close they are to the actual amount of consumption. The main advantage of empirical validation is that an approximately accurate standard truth model is the only method that can adequately represent the accuracy of the simulation software (Shrestha and Maxwell, 2006). However, weaknesses of this method include: (1) uncertainty with regards to input parameters, (2) the high financial and time costs associated with collecting detailed measurement data, and (3) a limited number of test cases (Judkoff et al., 2008).

These methods can be integrated to provide more reliable validation by reducing the disadvantages inherent in each method alone. Several researchers have introduced combinations of validation methods as a means of improving the accuracy of their analyses (Crawley et al., 2008; Henninger et al., 2003; Witte et al., 2001).

1.5.1.4. Validation of the CABE Performance Algorithm

To validate the CABE performance evaluation algorithm, this research conducted a number of comparative studies; the information on the base model was delivered by the U.S. Department of Energy (DOE) Commercial Reference Building Models of the National Building Stock (Deru et al., 2011). Test cases included different types of CABE models; the simulation results of the new CABE performance evaluation algorithm were compared with the results obtained from existing method to present its reliability and robustness.

1.5.2. Tools and Data

The overall process followed in this study can be divided into three parts: 1) parametric modeling, 2) performance analysis, and 3) multi-objective optimization. This section introduces the tools and data used in each to conduct this research.

1.5.2.1. Parametric Modeling

This research used Rhinoceros (McNeel, 2017), a 3D Non-Uniform Rational B-Spline (NURBS) modeling tool, and Grasshopper (McNeel, 2009), an open source visual programing environment for parametric modeling in Rhinoceros. These tools are the most widely used in parametric modeling, and provide plugins to support simulations and optimization. Parametric modeling in a visual programming environment can generate virtual building product models that include specific data sets such as building form. Users are able to parametrically change and regenerate the building model according to their needs.

1.5.2.2. Performance Analysis

There are several building energy and daylighting simulation tools used in this study. This research used Ladybug and Honeybee (Roudsari, 2014), open source graphical user interfaces that connect energy and daylighting simulation tools and are implemented in the Grasshopper visual programing environment. These tools are integrated with EnergyPlus (Version 8.6), a worldwide program for hourly whole-building energy simulation (Crawley et al., 2001a), RADIANCE, a backward ray-tracing algorithm for daylighting simulation (Ward and Rubinstein, 1988), and DAYSIM, a RADIANCE-based annual daylighting simulation tool (Reinhart and Walkenhorst, 2001). These implements have all been validated and are widely used in both research and practice.

1.5.2.3. Multi-objective optimization

Numerous optimization methodologies have been developed to deal with the single and multiple-objective problems that emerge during the decision-making steps in the building design process (Machairas et al., 2014). In this study, multiple conflicting objectives were addressed simultaneously. The Pareto front has widely been used to find sets of promising solutions to the Multi-Objective Optimization Problems (MOOPs) (Fonseca and Fleming, 1993). In this study, Octopus, a visual programming-based

MOOP solution for Grasshopper was utilized to support the decision-making process (Vierlinger and Bollinger, 2014).

1.6. Contributions to the Field

This research makes three contributions to the fields of parametric modeling research, performance-driven building design methodology, and multi-criteria optimization for CABE designs.

(1) A CABE model in a parametric design environment was able to represent its HBOO and support performance simulations.

(2) Conventional simulation tools were shown to successfully perform simulations of each CABE geometric state.

(3) Test cases of a CABE-based multi-criteria optimization process were able to assist in CABE-related design decisions, based on their performance.

Together, these three contributions show that the use of parametric modeling and simulation tools can help designers make better decisions about CABE alternatives.

1.7. Significance

This research is the foundation of a performance-driven CABE design method using parametric modeling, building performance simulation, and multi-criteria optimization. Designers are able to address four-dimensional CABE variables to support alternative decisions in the early design stages. Also, the algorithms are able to facilitate a more active use of CABE technology through performance management, something that is not supported by traditional methods. Finally, this study will lead to significant future research on CABE design, the development of CABE-friendly materials, and management of CABE operations guides.

1.8. Outline of the Chapters

This research is comprised of six chapters. *Chapter 1. Introduction* introduces and provides an overview of this study by describing the research problem, objective, and contributions. *Chapter 2. Research Agenda for Performance-driven CABE Design* uses a literature review to identify the performance-driven CABE research agenda, based on the procedure for CABE building performance simulations. *Chapter 3. A Model for Evaluating and Optimizing CABE Performance* describes the development of the new method for CABE performance evaluation. *Chapter 4. Validating the Parametric Behavior Maps (PBM) Method in CABE Performance Evaluations* presents test cases to validate the new method for CABE performance evaluation. *Chapter 5. An Optimization Framework for CABE Design Decisions* displays the multi-objective optimization framework with CABE system. *Chapter 6. Summary* summarizes the evidence for and contributions made by this research.

CHAPTER II

RESEARCH AGENDA FOR PERFORMANCE-DRIVEN CABE DESIGN

2.1. Overview

This chapter reviews the existing literature used to identify the research agenda for performance-driven CABE design. It is divided into three major categories, based on the procedure for creating Building Performance Simulations (BPSs) for CABE systems (see Figure 1): 1) storage of environmental factors, 2) production of CABE behavior schedules, and 3) simulation of the actuated CABE performance.

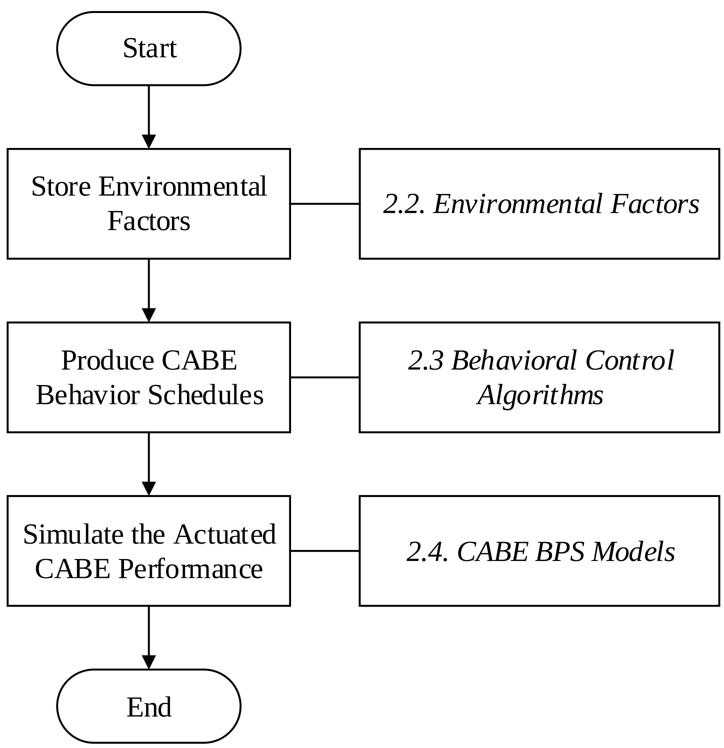


Figure 1. CABE BPS procedure and the contents of Chapter 2.

Below, section *2.2 Environmental Factors* introduces the environmental indicators that serve as triggers for CABE operation; the elements were included based on external environmental and occupant-oriented factors. The subsequent section, *2.3 Behavioral Control Algorithms*, reviews strategies in CABE BPS models that define the time variations of CABE configurations; also discussed are the thresholds for environmental factors used in previous studies and the methods of achieving optimum control scenarios. Section *2.4 CABE BPS Models* summarizes the current limitations of BPS methods for evaluating CABE performance. Finally, section *2.5 Summary of the CABE-Related Research Agenda* summaries the overall research agenda for performance-driven CABE design.

2.2. Environmental Factors

Performance-driven CABE design seeks to maintain a highly comfortable indoor environment while reducing energy demand, by adapting to changes in natural environmental forces and internal occupants' demands. Natural environmental forces are primarily related to climate data that constantly change throughout the year (Nielsen et al., 2011). Climate data have been used by designers to develop sustainable design strategies (Milne et al., 2007). Internal occupants' demands are represented in this research as Indoor Environmental Quality (IEQ), which consists of physical environmental factors such as natural light, view, indoor thermal conditions, visual satisfaction, and acoustic comfort (Al Horr et al., 2016). Organizations assigning credits for green building systems, such as the Leadership in Energy and Environmental Design

(LEED) program and Building Research Establishment Environmental Assessment Method (BREEAM), include IEQ as a category for ensuring occupants wellbeing (Al Horr et al., 2016). Thus, one of the most important roles for CABE technology is controlling environmental factors to meet occupants' range of comfort levels. This section reviews the external and occupant-oriented factors that can serve as triggers for CABE operation. Figure 2 includes a list of environmental factors for CABE-related behavioral control: (1) external environmental factors such as solar radiation, sun path, daylighting, and wind; and (2) occupant-oriented factors such as visual and thermal comfort.

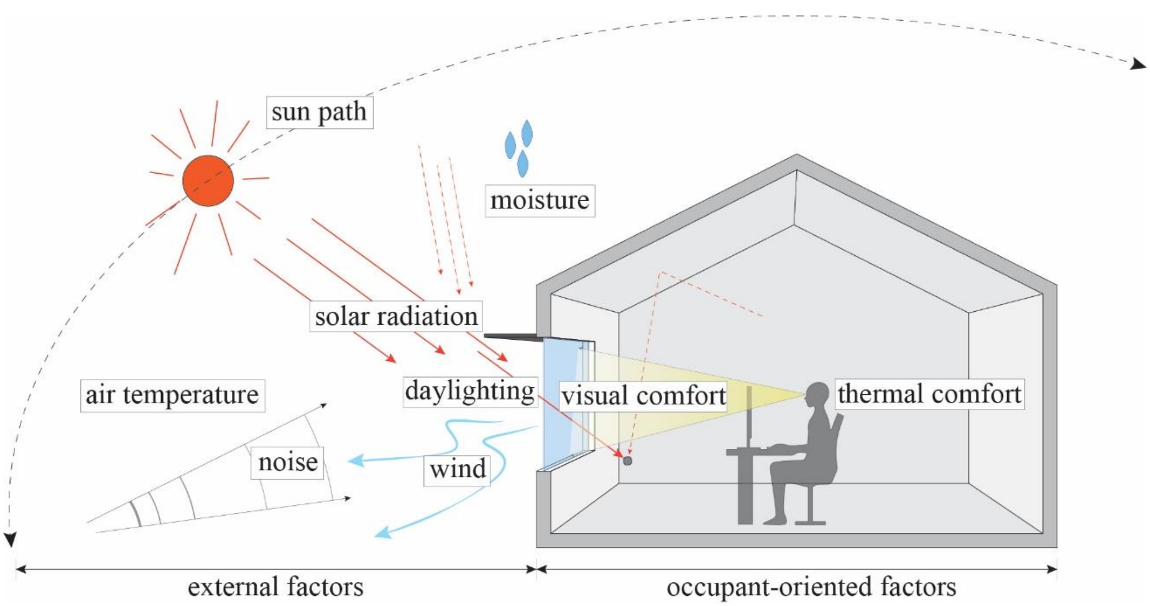


Figure 2. Environmental factors for CABE-related behavioral control.

2.2.1. External Environmental Factors

2.2.1.1. Solar Radiation

The management of solar gain via windows is the most important element of energy-efficient buildings with highly glazed envelopes; shading design is one possible strategy for managing incoming radiation, considering both energy and daylighting performance (Lomanowski and Wright, 2009; Maestre et al., 2015). In many situations, CABE designs can directly (and thus more efficiently) respond to the hourly, daily, monthly, and seasonal changes in the amount of solar radiation, by changing their geometric states or material properties (Kasinalis et al., 2014).

Solar radiation consists of three types: beam (direct), diffuse, and reflected. Beam radiation is shortwave solar energy that reaches the surface of the earth in a parallel line originating from the sun. Diffuse radiation is scattered in random directions by air molecules and particles in the atmosphere. Reflected radiation is the solar radiation reflected from non-atmospheric elements such as the ground or other surroundings (Duffie and Beckman, 2013). Although the ratio of beam to diffuse radiation generally varies based on the sky's conditions, sun's position, and latitude, beam radiation accounts for the major portion of solar energy when the position of the sun is high in a clear sky (Naqi, 2007). The portion of radiation reflected from buildings and the ground, however, becomes larger in highly dense urban environments, especially in overcast sky conditions (Lou et al., 2016). Thus, control strategies for incoming beam and diffuse radiation should be developed to identify optimal CABE designs, considering the sky conditions, building orientation, and surrounding environment.

2.2.1.2. Sun Path

The sun's path plays a key role in determining shading design strategies (Szokolay, 1996). As illustrated in Figures 3A and 3B, the Horizontal Shadow Angle (HSA) and Vertical Shadow Angle (VSA) are used to determine the appropriate dimensions of shading devices such as vertical fins and overhangs (Grondzik et al., 2010). The main reason for determining HSA and VSA values is to block beam radiation using passive shading strategies; these values can easily be calculated using the building's orientation and azimuth of the sun's position at the desired dates and times (Szokolay, 1996). Sun path diagrams and shading masks have widely been used by designers and researchers as a graphical method for estimating the effects of shading (Kensek et al., 1996; Marsh, 2005). Although HAS and VSA values can be integrated into simple CABE shapes in parametric modeling, this integration cannot produce analytical information suitable for determining CABE performance with complex geometry (Kim et al., 2015). Figure 3C illustrates an example of a complex CABE installed in the Al Bahr towers in Abu Dhabi (Oborn, 2012), and limitations on its control using HAS and VAS. The limitations originate from the lack of a relationship between these values and the complex CABE.

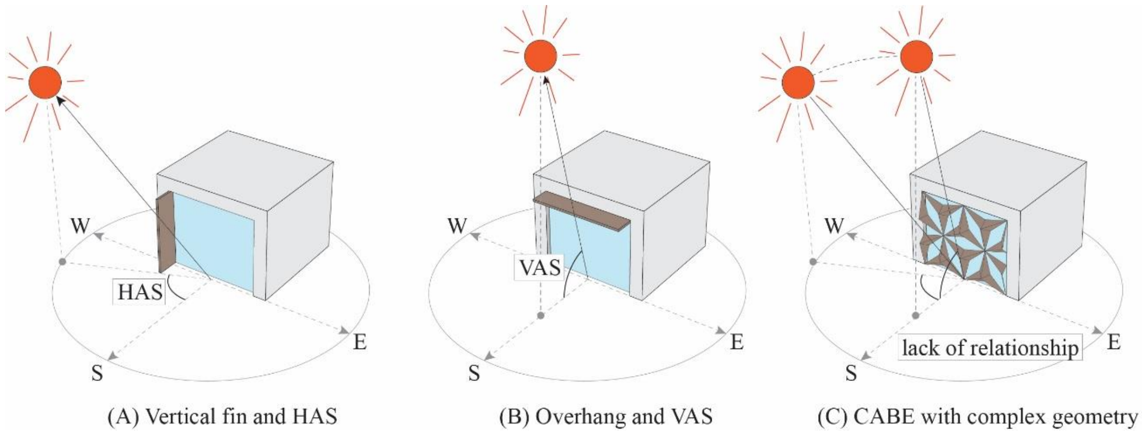


Figure 3. Relationship between CABE and HAS and VAS values (Kim et al., 2015).

A CABE with complex geometry can be controlled in relationship to the sun's path. The angle of incidence of beam radiation is defined as the angle between the normal vector of a given surface and the vector of beam radiation, as described in Figure 4A (Szokolay, 1996). For example, angles of incidence of 0° and 90° indicate that a given surface directly faces the sun, and the normal vector and the sun's vector are perpendicular (see Figure 4B and 4C). This means that the surface receives only diffuse and reflected radiation without beam radiation when the incidence angle becomes 90°. Thus, the integration of the angle of incidence into a CABE's opening ratio would enable direct control of incoming solar radiation. To this extent, Kim et al. (2015) presented a method for controlling the degree of openness of a CABE with complex geometry based on the angle of incidence, using a parametric BIM model and the sun's path. The benefit of this method for controlling a CABE is its ease in managing its HBOO, regardless of the CABE's complexity or the building's orientation.

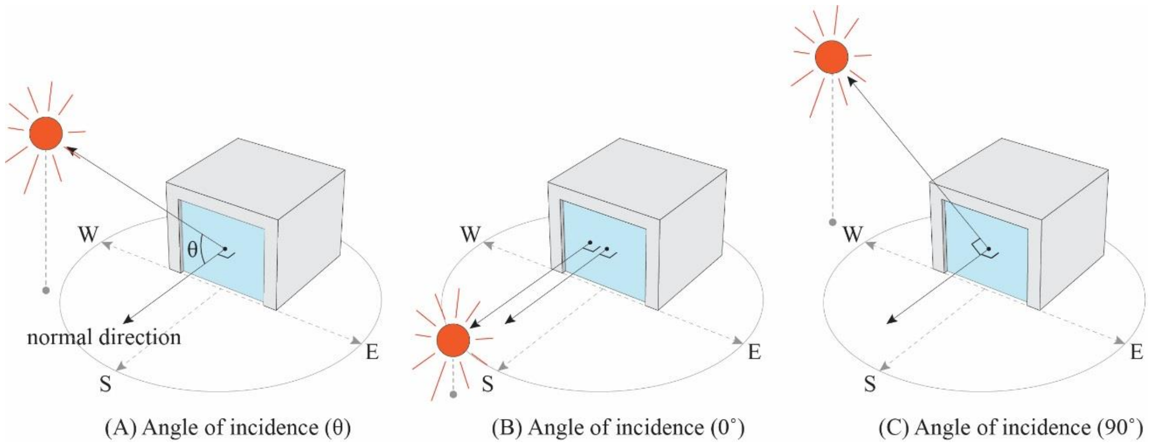


Figure 4. The angle of incidence with a vertical surface (Kim et al., 2015).

2.2.1.3. Daylighting

Suitable daylighting levels in a given space can reduce energy consumption for artificial lighting and heating and cooling loads. They can also increase the quality of the indoor environment, resulting in positive effects on occupants' comfort, health, and productivity (Yu and Su, 2015). There are two aspects to evaluating daylighting performance: quantitative and qualitative. The respective indexes were developed based on illuminance and glare analysis (Cantin and Dubois, 2011). This section reviews the quantitative aspect of daylighting as one of the external environmental factors affecting CABE operation. The qualitative aspect is addressed in the section on occupant-oriented factors (visual comfort).

Illuminance is a widely-used photometric quantity defined as the total luminous flux incident falling onto a given surface; it is measured in lumens per unit area, as lux (Reinhart, 2014). The Illuminating Engineering Society of North America (IESNA) provides a recommended illuminance level as a daylighting design criterion (DiLaura et al., 2011). Generally, a suitable illuminance level for an office space ranges from 500 to 1,000 lux, based on the level of work activity and other guidelines; details can be found in the IES handbook (DiLaura et al., 2011).

Computational simulation tools have been developed for the modeling and simulation of daylighting performance; these tools are based on ray-tracing, radiosity, and photon maps, and are widely used in various studies of building science (Ochoa et al., 2012). Radiance, a backward ray-tracing algorithm, is the most popular validated daylighting simulation tool developed by Ward (1994). Daysim, developed by Reinhart and Walkenhorst (2001), is a radiance-based annual daylighting simulation tool integrated with local climate data and daylighting coefficients. Daysim has been used to investigate the influence of automated blinds systems triggered by external environmental factors on reducing energy consumption for artificial light and increasing occupants' comfort (Athienitis and Tzempelikos, 2002; Reinhart and Walkenhorst, 2001; Wienold, 2009).

Several daylighting availability metrics have been developed to evaluate daylighting performance in a given space. Daylighting Factor (DF) is defined as the ratio of indoor illuminance at a given point under an overcast sky to the outdoor illuminance as measured under the same sky, without obstructions. This factor includes the Sky Component (SC), which is direct light from the sky (sky-diffuse), Externally Reflected Component (ERC), and Internally Reflected Component (IRC), which represent the reflected light from the external and internal built environments, respectively (Hopkinson et al., 1966). DF can also be measured from a reference point on a vertical window excluding IRC; in this case it is named the Vertical Daylighting Factor (VDF) and is used to analyze the potential daylighting availability from that window (Cheung and Chung, 2005). From the VDF value, the Vertical Sky Component (VSC) only includes direct light from the sky; it can be used to investigate the impact of the surroundings (Littlefair, 2011).

The recommended range of average and minimum DF values are 5 percent and 2 percent for offices, respectively (Li and Lam, 2001). In Hong Kong, the Building (Planning) Regulations CAP123 - Lighting and Ventilation recommends 8 percent and 4 percent VDF for habitable rooms and kitchens (Ng, 2003). The BREEAM recommendation is to achieve more than 27 percent VSC for suitable daylighting performance in London (Littlefair, 2011). DF-based metrics provide estimates under the International Commission on Illumination overcast skies (Li et al., 2017). These metrics are not able to represent dynamic daylighting performance with more realistic climate conditions, due to their simplicity; the result is a loss of accuracy (Mardaljevic, 2000).

Climate-Based Daylighting Modeling is a type of daylighting performance prediction model that uses a full year of meteorological data, including data for various sky conditions; this enables performance evaluations of various shading types and control strategies (Mardaljevic et al., 2009). Daylight Autonomy (DA) is defined as the percentage of occupied hours in a year when the value of a measuring point in a space is above a certain target illuminance level (Reinhart and Walkenhorst, 2001). Currently, IESNA recommends 50 percent DA with a target of 300 lux for workplaces in offices, classrooms, and meeting rooms (DiLaura et al., 2011). To avoid insufficient or excessive daylighting, Useful Daylighting Illuminance (UDI), developed by Nabil and Mardaljevic (2006), is widely employed. It includes lower and upper thresholds in order to divide the domain of annual illuminance into three categories. Generally, the lower and upper thresholds are set at 100 lux and 2,000 lux, respectively. For example, a recommended daylighting performance is higher than 80 percent of UDI (100-2,000 lux) (Piderit Moreno and Labarca, 2015). Spatial Daylighting Autonomy (sDA) is defined as the percentage of floor area that meets the target illuminance level for occupied hours in one year; it is calculated by counting the number of illuminance measuring points that meet the requirements (Heschong et al., 2012). LEED v4 recommends that at least 55 percent of regularly occupied floor area should meet a minimum 300lux illuminance level for 50 percent of the annual occupied hours ($sDA_{300/50\%}$) (USGBC, 2013). Annual Sunlight Exposure (ASE) describes excessive sunlight exposure that is defined by the percentage of space that exceeds a recommended illuminance level for the specified occupied hours (Heschong et al., 2012). LEED recommends that no more than 10 percent of regularly occupied floor area exceed 1,000lux for 250 annual occupied hours (USGBC, 2013). Table 1 summarizes the daylighting metrics and examples of recommendations discussed above. These metrics are widely-used daylighting availability indexes that can serve as CABE behavior control factors to achieve optimum daylighting performance.

Table 1. Summary of Daylighting Metrics and Recommendations

Daylighting Metrics	Recommendations
Daylighting Factor (DF)	5% (average) and 2% (minimum) for offices ≤ DF
Vertical Daylighting Factor (VDF)	8% (habitable rooms in Hong Kong) ≤ VDF
Vertical Sky Component (VSC)	27% (London) ≤ VSC
Daylight Autonomy (DA)	50% (target: 300 lux for offices) ≤ DA
Useful Daylighting Illuminance (UDI)	80% (classrooms) ≤ UDI (100-2,000 lux)
Spatial Daylighting Autonomy (sDA)	55% ≤ $sDA_{300/50\%}$
Annual Sunlight Exposure (ASE)	$ASE_{1000/250}$ ≤ 10%

2.2.1.4. Wind

Natural ventilation is one of the most efficient passive design methods for reducing energy demands related to air conditioning and improving occupants' thermal comfort, productivity, and indoor air quality (Qian and Yang, 2016). The development of simulation technology has allowed for more accurate predictions of energy use and indoor environment quality by integrating Computational Fluid Dynamics with a thermal analysis model (Zhai and Chen, 2005). Although the need to integrate natural ventilation at the early design stage has increased, there are still only limited opportunities to implement natural ventilation due to the complex physics and uncertainty of air flow (Passe and Battaglia, 2015).

Natural ventilation can be achieved without mechanical systems by applying suitable passive design strategies. The principle of natural ventilation is the use of changes in air flow patterns based on pressure and temperature differences between the inside and outside of buildings (Qian and Yang, 2016); its implementation in building design has taken various architectural and spatial shapes such as caves, courtyards, arcades, wind catchers, and chimneys (Passe and Battaglia, 2015). As examples of contemporary architecture, the San Francisco Federal Building (McConahey et al., 2002), GSW building (Kleiven, 2003), and Commerzbank Tower (Guy and Moore, 2007) all actively applied natural ventilation strategies. In addition, research on building envelopes has verified the efficacy of the use of natural ventilation principles for increasing indoor air flow by adapting the various physics of natural phenomena, such as the stack and Venturi effects (Blocken et al., 2011; Lomas, 2007).

As air inlets and outlets, the proportion of openings plays a significant role in generating natural ventilation, as well as integrating natural ventilation principles and control strategies. Generally, user controlled or automated operable double-skin envelope systems are applied to curtain walls and skylights for natural ventilation in urban environments (Passe and Battaglia, 2015). Recently, prototypes using advanced smart materials have been developed to increase natural ventilation in free-cooling CABE systems (Xiang and Zhou, 2015). However, their application on a building scale is still in the initial stages, due to a lack of available natural resources and uncertainty in surrounding climate prediction in an urban environment (Passe and Battaglia, 2015). Nevertheless, CABE technology can be combined with advanced systems to flexibly respond to changes in wind direction and velocity so that the positions of inlets and outlets adapt to the environment and increase opportunities for natural ventilation (Passe and Battaglia, 2015).

2.2.2. Occupant-Oriented Factors

In terms of user satisfaction, the best strategy is to design and operate a CABE that is focused on occupants' demands. In other words, a real-time feedback loop between sensing an occupant's demands and actuating a CABE response is the ideal way of adapting to the physical environment around a building. Occupants' demands can be represented as levels of human comfort in a room, comprised of three factors: thermal, visual, and acoustic. These factors are related to subjective measurements of satisfaction with regards to various physical environmental elements (Oral et al., 2004). In this sense, when the human comfort level does not fall within a comfortable range, a CABE can change its state to increase users' satisfaction. This section focuses on a review of thermal and visual comfort as factors for CABE behavior control.

2.2.2.1. Thermal Comfort

Thermal comfort is measured by subjective evaluation and expressed as the satisfaction with the thermal environment (ASHRAE, 2010). Fanger (1972) developed thermal comfort prediction indexes called the Predicted Mean Vote (PMV) and Predicted Percent Dissatisfied (PPD); their parameters include air temperature, mean radiant temperature, air velocity, relative humidity, metabolic rate, and clothing insulation in climate chambers. PMV consists of a seven-point sensation scale ranging from Cold (-3) to Hot (+3). PPD is calculated based on the PMV value; it represents the percentage of occupants who feel dissatisfied. American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) recommends that the comfortable indoor spaces range from -0.5 to 0.5 for PMV, and less than 10 percent for PPD (ASHRAE, 2010). Although the PMV and PPD methods have widely been used to evaluate indoor thermal conditions, the indexes perform well only in spaces controlled by Heating, Ventilation, and Air Conditioning (HVAC) systems (Van Hoof, 2008). Since the range of comfortable temperatures is so narrow, the model cannot fully cover the dynamic environment created by natural ventilation (Passe and Battaglia, 2015).

The adaptive thermal comfort model was developed for natural ventilated buildings, as a means of overcoming the limitations of PMV; it includes changes in human behavior done to adapt the environment, such as opening windows or changing clothing and activity levels (de Dear et al., 1998; Nicol et al., 2012). ASHRAE defined the adaptive thermal comfort model as “a model that relates indoor design temperatures or acceptable temperature ranges to outdoor meteorological or climatological parameters” (Nicol et al., 2012). The main contribution of the adaptive thermal comfort model is to extend the range of the comfortable zone so that passive design options can be evaluated in terms of thermal comfort in built environments without mechanical cooling systems (Passe and Battaglia, 2015).

The level of thermal comfort can be enhanced by properly introducing a CABE system, especially when natural ventilation and passive cooling strategies are applied. For example, if CABE operation enables an increase in incoming air velocity in a naturally ventilated building, the range of indoor operative temperatures in the thermal comfort zone of the adaptive model is extended accordingly, resulting in energy savings related to cooling demands. Similarly, the human behavior prediction model related to metabolic rate, clothing, and how frequently windows are opened can be potentially integrated with CABE performance evaluation and operation strategies. Table 2 summarizes the thermal comfort index and the standards developed by ASHRAE (2010).

Table 2. Summary of Thermal Comfort Metrics and Recommendations (ASHRAE, 2010)

Thermal Comfort Index	Standards
Predicted Mean Vote (PMV)	$-0.5 \leq \text{PMV} \leq 0.5$
Predicted Percent Dissatisfied (PPD)	$\text{PPD} \leq 10\%$
Adaptive Model	23.3°C ≤ Indoor operative temperature ≤ 30.3°C (80% acceptability limits)

2.2.2.2. Visual Comfort

Ensuring appropriate natural lighting and views of the outdoors are key elements for providing occupants with visual comfort. CABE systems can control the amount of incoming daylighting and the view based on necessity over time. As a qualitative aspect of daylighting performance, visual comfort is measured by a glare index that represents the level of physical discomfort within the visible field; excessive incoming direct and reflected daylight via windows cause discomfort or an inability to see objects, due to the luminance difference between the human vision of objects (e.g., a computer screen) and their surroundings (Hopkinson, 1972). Thus, the level of discomfort varies based on the observer's position, orientation of the sun, sky luminance, and opening size. Glare can be categorized into two types: disability and discomfort. Disability glare indicates an inability to see objects that can be evaluated objectively; discomfort glare demonstrates a subjective measurement of feeling uncomfortable, even though the objective can be seen. Daylighting Glare Index (DGI) and Daylighting Glare Probability (DGP), developed by Hopkinson (1972) and Wienold and Christoffersen (2006), respectively, are the most common metrics for evaluating discomfort glare (McNeil and Burrell, 2016).

Various studies have developed formulas and tools to evaluate glare (Carlucci et al., 2015b). DGI includes large glare sources such as windows; the threshold of maximum acceptable glare for office work has a value of 22 in the DGI (Chaiwiwatworakul et al., 2009). Application of the DGI is not available under conditions of direct sunlight; DGP is the most reliable metric under a number of daylighting situations (McNeil and Burrell, 2016). Table 3 shows the range of DGI and DGP values based on their discomfort classifications (Jakubiec and Reinhart, 2012; Wienold and Christoffersen, 2006).

Table 3. Glare Metrics and Subject Rating (Jakubiec and Reinhart, 2012; Wienold and Christoffersen, 2006)

Discomfort Classification	DGI Value Range	DGP Value Range
Imperceptible glare	< 18	< 0.35
Perceptible glare	18 – 24	0.35 – 0.40
Disturbing glare	24 – 31	0.40 – 0.45
Intolerable glare	> 31	> 0.45

Although efforts to develop measurement methods for glare have broadly been studied, in terms of its reliability critical challenges remain. The outcomes are significantly related to individual perception, position of the observation, and a wide range of assessed luminance (Carlucci et al., 2015b).

In terms of evaluating the view of the outdoors, there are two categories: qualitative and quantitative. Qualitative value is highly related to the surrounding conditions, such as the presence of parks, forests, mountains, and lakes (Michael et al., 2002). Quantitative value is considered more important in highly dense high-rise built environments, due to its relevance to the degree of openness towards the outdoors, ensuring daylighting and views of outdoor scenery (Al Horr et al., 2016). The quantitative value of view can be represented as the visible sky ratio at a measuring point. Several methods have been developed to evaluate the visible sky ratio, based on: 1) 2D projections, 2) 3D sky segmentation, and 3) DF-based approaches calculating the total amount of visible sky (Yi and Kim, 2017). LEED has also offered credits for views achieving a direct line of sight to the outdoors through windows that together measure greater than 75 percent of all regularly occupied floor area (USGBC, 2013). However, more detailed indexes and recommendations for evaluating views for CABE buildings must be developed.

Despite dependency on occupant preference of indexes of glare and views of the outside, research in this field has tried to increase their reliability and robustness. In this regard, the integration of a visual comfort index, human behavior, and CABE design and operation may produce better solutions for increasing IEQ.

2.3. Behavioral Control Algorithms

There are different goals associated with managing each environmental factor affecting CABE operation, and sometimes these goals conflict. For example, CABE behaviors in response to solar radiation tend to result in shading devices being closed to reduce energy consumption for air conditioning; however, this also means that more energy is consumed for artificial lighting. Also, this produces totally opposite behavior patterns based on season (e.g., summer and winter), building location (e.g., northern or southern hemispheres), and orientation. Furthermore, in CABE performance evaluation and practice, simultaneous consideration of multiple factors and the selection of optimum behaviors can be deeply complex (Loonen et al., 2017). Thus, the effects of CABE technology can differ significantly depending on the environmental factors and their selected thresholds (set points) in the shading control algorithm (Lee and Tavil, 2007; Poirazis et al., 2008). In this regard, this process of selection identifies a potential future research agenda that will contribute to improved performance-driven CABE designs and the development of more advanced smart materials.

2.3.1. Behavior Control Factors and their Thresholds in the BPS Model

In past decades, various studies have been conducted to determine the efficacy of using shading control modes in BPS models. Generally, shading control algorithms consist of two steps: choosing environmental factors to act as indicators and setting thresholds for actuation. In term of choice of factors, one or multiple parameters can be used based on the research objectives and practices. Similarly, one or multiple thresholds for each factor can be assigned to generate the operation schedule of the shading device. The use of one or multiple thresholds results in either binary or multiple shading states. In other words, the binary state of the shading represents a fully open or closed shading device when the values of the factors are higher or lower than the threshold. Otherwise, the shading maintains a designated state. The use of multiple thresholds enables the shading to gradually change its state from fully opened to fully closed so that it can more flexibly respond to the environment.

Table 4 presents a list of factors and their thresholds obtained from the existing literature on shading control, including shading type and test location. For example, the amount of transmitted beam irradiation was assigned as an environmental factor with a threshold to define a binary state; the shading was fully lowered when the incoming irradiation exceeded 20W/m^2 in Los Angeles and Chicago (Shen and Tzempelikos, 2012), 50W/m^2 in Toronto (Reinhart, 2004), and 94.5W/m2 in Los Angeles (Lee and Selkowitz, 1994). Indoor temperature also has been used as a factor with a threshold of 25°C (Moeseke et al., 2007) and 24°C (Nielsen et al., 2011) for the binary state. Multiple thresholds of incident angles of solar irradiation were used to control shading devices with multiple states (Kim et al., 2015; Sun et al., 2010).

In terms of multiple-factor sensing, the internal temperature and total incident irradiation (Moeseke et al., 2007), internal temperature and glare index (Nielsen et al., 2011), and transmitted radiation and glare were considered when generating the shading operation schedule. Moeseke et al. (2007) concluded that considering multiple factors for shading control was a more efficient strategy than reviewing one factor alone. However, more efficient control options could exist and the results vary depending on the climate conditions, orientation, and glazing and shading properties (Tzempelikos and Shen, 2013).

Table 4. List of Environmental Factors and their Thresholds

	Factors and Thresholds	Behavior Type	Shading Type	Location	Resource
Single factor	$20W/m^2 \leq$ transmitted beam radiation	Binary state (fully closed)	Roller shades	LA & Chicago	Shen and Tzempelikos (2012)
	$50W/m^2 \leq$ transmitted beam radiation		Venetian blinds	Toronto	Reinhart (2004)
	Linear regression of opening ratio with solar incidence angle	Multiple states of openness	Blinds	Abu Dhabi	Sun et al. (2010)
			Complex shading		Kim et al. (2015)
Multiple factors	$94.5W/m^2 \leq$ transmitted beam radiation or $20 <$ Hopkins glare index	Binary state (fully lowered)	Venetian blinds (indoor)	LA	Lee and Selkowitz (1994)
	$24°C \leq$ indoor air temperature and intolerable $<$ DGP		Venetian blinds (indoor)	Denmark	Nielsen et al. (2011)
	$22\sim25°C \leq$ indoor air temperature and $0 \leq$ total radiation on the façade $\leq 500W/m^2$		External mobile screen	Belgium	Moeseke et al. (2007)

CABE behavior patterns play a key role in estimations of their performance. The existing literature on BPSs and CABEs has estimated CABE performance based on two types of behavior patterns (regardless whether single or multiple factors are employed): binary or multiple degrees of openness (see Figure 5). More than two behavior patterns were used separately when considering multiple environmental factors. However, as shown in Figure 5B, the relationships among the environmental factors and degree of openness of the CABE were represented as a linear regression, which might have missed better, more efficient behavior options. This becomes an even more complex problem when considering CABE structures with complex geometries such as the Al Bahr Towers in Figure 3C.

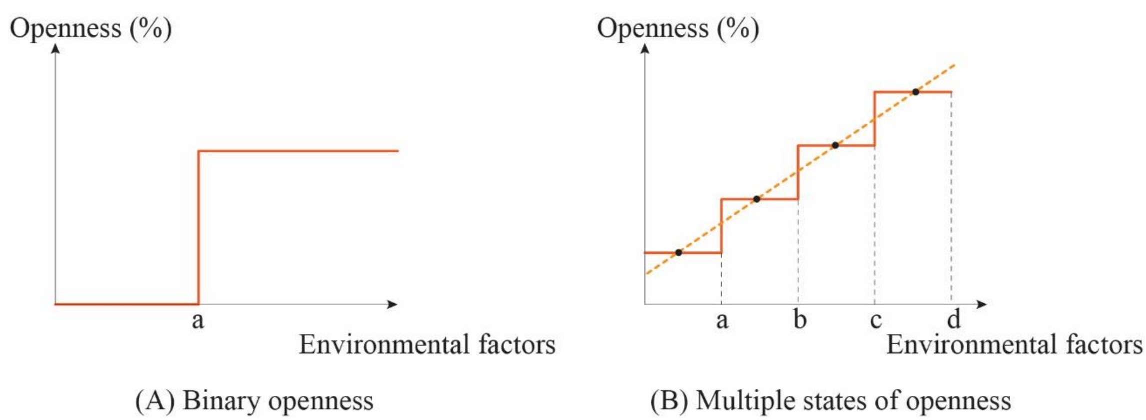


Figure 5. CABE behavior types in the BPS model.

2.3.2. Self-Adapting Controls in Practice

Recently, innovations in simulation technology, materials, and fabrication methods have enabled architects to explore the potential application of biomimetic principles to CABE design, using the concept of self-adapting controls (Badarnah Kadri, 2012; Lopez et al., 2015; Mazzoleni and Price, 2013). Advanced materials respond to changes in the environment by deforming their properties based on an embedded sensing factor and its thresholds. The benefits of using smart materials in CABE designs is that there is no need for operation energy or complex mechanical devices to generate transformations (Lopez et al., 2015).

Although there is currently only a small number of building-scale CABE systems that use smart materials, several researchers have attempted to develop CABE prototypes with such materials based on embedded factors and thresholds (see Table 5). Sung (2013) developed Bloom, a CABE prototype, using thermo-bimetal panels that consist of different expansion coefficients; it gradually closed and opened based on temperature changes ranging from 55°F (fully closed) to 85°F (fully open), increasing natural ventilation. Similarly, Payne (2013) used a custom manufactured Shape Memory Alloy (SMA) wire to open and close a CABE prototype; the length of the SMA wire increased or contracted based on temperature differences ranging from 60°F to 80°F. Using a programmable maple veneer, Reichert et al. (2015) developed a hygroscopic actuation-based CABE prototype with apertures that changed their configuration based on relative humidity values ranging from 30RH% to 90RH%. Finally, a CABE system for evaporation cooling was developed using hydrogel that could contain water up to 40 times its volume and consequently cool down its surroundings (Mitrofanova et al., 2013).

Table 5. Factors and Thresholds of Smart Materials

Smart Materials	Factors and Thresholds	Resource
Thermo-bimetal	Temperature: 55°F (closed) to 85°F (open)	Sung (2013)
Shape memory alloy	Temperature: 60°F (closed) to 80°F (open)	Payne (2013)
Programmable veneer	Humidity: 80±3%RH (closed) to 40±3%RH (open)	Reichert et al. (2015)
Hydrogel	Moisture: water absorption (400 times its volume)	Mitrofanova et al. (2013)

Although the development of CABE prototypes using smart materials has the potential to be applied to real buildings for energy savings, only a limited number of studies have integrated a BPS model to investigate their efficacy. In other words, previous studies have focused on the development of physical behavior patterns based on thresholds embedded in the smart materials, and their performances have roughly been estimated. More analysis is required to define the information embedded in the thresholds when considering the performance of CABEs using these types of constituents. The different threshold domains of smart materials may produce different outcomes in BPSs; the domains vary based on climate, surrounding conditions, and building orientation. Thus, well-defined threshold information should be collected via the integration of the CABE design with a BPS model before development of the smart material. This will contribute to interdisciplinary research joining the fields of architecture and materials science.

2.3.3. Advanced CABE Behavior Model

As discussed in the previous section, the main challenge with controlling CABE behavior in BPSs is how to define a suitable relationship between the environmental factors and their thresholds, focusing on a given condition. Well-defined CABE behaviors produce better building performance outcomes as compared to conventional behavior methods. To solve this challenge, two tasks must be accomplished:

(1) Various linear or non-linear regressions must be created to compare the CABE's level of openness and the domains of the thresholds generating the CABE's behavior patterns; and

(2) Multiple environmental patterns must be considered simultaneously during the CABE's behavior generation process to balance conflicting benefits.

For example, as described in Figure 6, a numerical model (either linear or non-linear regression) can generate CABE operation behavior scenarios (schedules) integrated with one or multiple environmental factors; the scenarios are used to simulate the BPS model of the CABE system. The question at this stage is how to make decisions about the CABE behavior scenarios that will be optimal for the BPS process, by addressing the various variables related to environmental factors. To this extent, this section briefly reviews two decision-making approaches that help generate optimized scenarios in BPSs at the early design stages: optimization and statistical analysis.

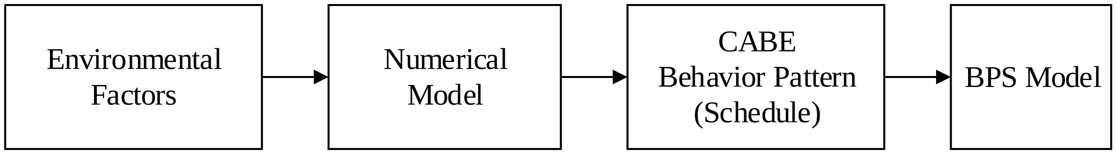


Figure 6. BPS procedure with advanced CABE behavior model.

2.3.3.1. Optimization Approaches

Optimization processes seek minimum or maximum values related to an objective function, based on various variables and constraints; a number of geometrical (building mass, orientation, form, etc.) and non-geometrical (HVAC systems, building controls, etc.) issues have been addressed with single or multiple objective optimization methods to solve BPS-related problems (Machairas et al., 2014). The integration of optimization methods does not necessarily find the “best” solution; the goal is to identify better alternatives by exploring a large search space with regards to parametric variations (Attia et al., 2013).

CABE technology aims to achieve multiple and often conflicting objectives, such as minimizing energy consumption and providing comfortable indoor daylighting conditions. In fact, most problems in the real world simultaneously address conflicting objectives to achieve satisfactory solutions (i.e., minimizing cost while maximizing profits) (Konak et al., 2006). Multi-Objective Optimization Problems (MOOPs) in performance-driven building design encounter various fitness functions with diverse variables in order to find a set of solutions that represent good trade-offs between competing objectives (Carlucci et al., 2015a). A Pareto-optimal set indicates a non-dominated solution set within the entire feasible solution space; the Pareto-optimal front corresponds to the boundary of the feasible objective space within which objective functions are intended to be minimized (see Figure 7). The goal of Multi-Objective Optimization (MOO) is to provide a set of solutions as close as possible to the Pareto-optimal front (Konak et al., 2006).

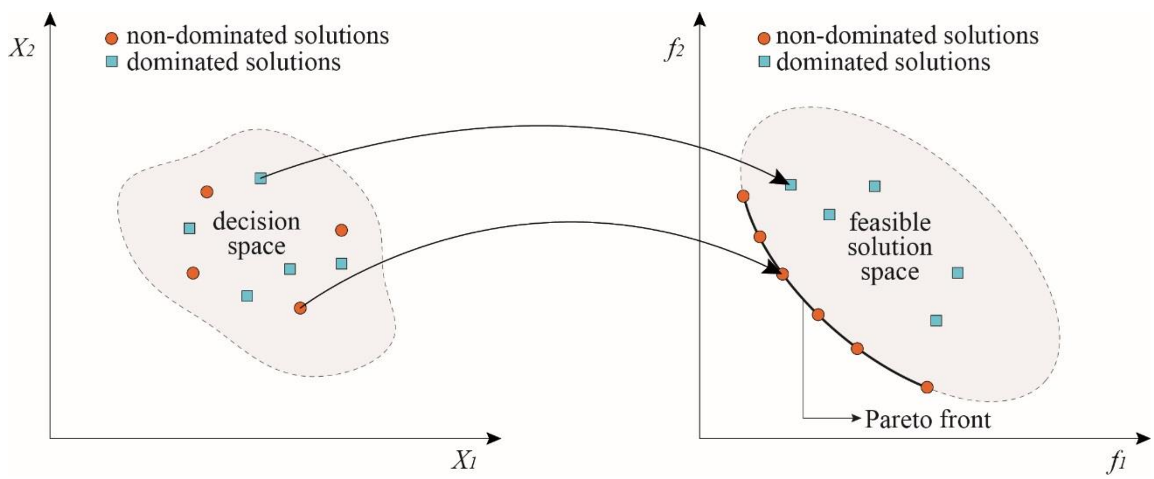


Figure 7. Example of a Pareto front set (Cámara et al., 2012; Jaimes et al., 2011).

MOO methods can be divided into two categories: (1) classical and (2) non-traditional (Shukla et al., 2005). Classical methods aggregate MOOPs into a single objective problem using mathematical principles to find solutions (Zitzler, 1999). The Weighting Method, a widely used classical technique, converts MOOPs into a single scalar objective by multiplying each objective with a user-provided weight (Marler and Arora, 2010). Although it is easier to use classical methods when solving MOOPs, there are several disadvantages: (1) limitations when solving non-convex MOOPs, (2) restricted application areas, and (3) multiple optimization runs (Zitzler, 1999).

Evolutionary Multi-objective Optimization (EMO), a non-traditional method, follows stochastic rules that mimic natural evolution in order to find a set of Pareto-optimal solutions (Shukla et al., 2005). The main advantages of EMO over classical methods are: (1) a single optimization can generate multiple trade-offs, and (2) a larger search space can be addressed (Zitzler, 1999).

Although the main challenge in BPS optimization is the computational expense of considering complex problems, the process helps designers explore various design options and find the most promising solutions. In terms of the parametric modeling process, CABE design variables include a large number of geometric transformations and their behaviors over time. To this extent, new optimization models are needed to further consider the close relationship between CABE design and operation (Loonen et al., 2017).

2.3.3.2. Statistical Approaches

The BPS modeling process includes various and complex input variations. During this process, some non-determined or uncertain input variables such as occupant behavior and unpredictable weather are determined based on the engineer's knowledge and experience, resulting in a decrease in the reliability of the outcomes. Statistical approaches such as uncertainty and sensitivity analyses have widely been used to identify uncertainty issues in BPS research to address a large solution space; this approach provides statistical information about the outcomes that helps designers make rational decisions in the early design phase, as well as in the more detailed construction stages (Heiselberg et al., 2009; Hopfe and Hensen, 2011; Tian, 2013). Design decisions considering BPS uncertainties are less straightforward than deterministic calculations. However, the integration of uncertainty analysis into BPSs increases the reliability of the outcomes and robustness of the designs by providing a range of possible performance indicators; it considers combinations of design parameters, systems, and controls (Østergård et al., 2016).

Sensitivity analysis has also been used to identify the most influential input variations that impact outcomes; designers primarily focus on these parameters to produce better design options and conduct optimization processes (Østergård et al., 2016). The use of this approach allows designers to: 1) use simplified but robust BPS models by implementing parameter screening, and 2) answer "what-if" questions when investigating various design options as a means of design support (Hopfe and Hensen, 2011). In terms of CABE design and operation, Loonen and Hensen (2013) presented a dynamic sensitivity analysis to address time-series performance aspects. Compared to conventional methods, their process provided more detailed information about the impact of shading parameters over time that could potentially be used in CABE operations. The advanced integration of uncertainty and sensitivity analyses into CABE systems has the considerable potential to identify the most important CABE variables and support better-informed decisions about CABE designs, especially with regards to occupant behavior and unpredictable weather conditions (Loonen et al., 2017).

2.4. CABE BPS Models

In terms of modeling and simulation, the main characteristics of CABE systems include changes to their geometric states and material properties over time; the major concern for a BPS model is how to precisely represent these changes when evaluating CABE performance (Loonen et al., 2017). Although CABE systems attempt to improve the quality of the indoor environment in response to various environmental factors, the most popular research topic in the field of architecture is generally evaluating the thermal performances of integrated CABE systems. For this reason, the following section reviews the current limitations and challenges in energy modeling and simulation with CABE technology, and introduces the existing approaches attempting to overcome these issues.

2.4.1. Limitations to BPS tools

Most BPS tools have been developed and updated with a focus on performance predictions of static building models (Loonen et al., 2017). Although they have limited functionality with regards to representing state changes to CABE systems over time, their applications are very restricted. For example, EnergyPlus, a widely-used whole-building energy simulation tool, provides various CABE control types by integrating environmental factors such as solar radiation, outside and zone air temperature, the daylight glare index, and zone heating and cooling loads; users can develop their own CABE operation scenarios by setting environmental factors and their thresholds for evaluating CABE performance. However, various control types are available, with the following restrictions (DOE, 2010):

- They only support simple types of CABEs such as venetian blinds, screens, and pull-down shades;
- Such functions evaluate performance by determining when shading devices are only fully “on” (covering all the windows) or “off” (covering none of the windows); and
- The shading devices should follow the shape of the window because their locations (interior, exterior, or between-glass) are determined with hierarchical relationships associated with windows in the BPS tool.

These limitations of the energy simulation tools have been discussed in several studies (Atzeri et al., 2013; Choi et al., 2017; Kim et al., 2015; Kim et al., 2016; Lee et al., 2016; Loonen et al., 2017); they can be summarized as follows:

- It is difficult to integrate energy simulation and complex 3D CABE geometry, considering the aesthetic aspects of building design.
- The limited control behavior (fully “open” or “closed") does not incorporate a large number of design options that might offer better solutions.
- High levels of knowledge and experience with BPSs are required to test the performance of CABEs, resulting in dependency of designers upon simulation experts and potentially reduced cooperation between designers and simulation experts at the early design phases.

2.4.2. Existing Approaches and their Limitations

BPS tools' inability to evaluate CABE performance accelerated the development of new methods to overcome these limitations. Since current BPS tools do not fully support CABE behavior, these emerging methods explore how CABE behaviors are represented in current BPS tools. As summarized in Table 6, CABE-related BPS strategies can be categorized based on the number of CABE states and their behavior frequency. The main idea is to use multiple BPS models with static shading for independent simulations, creating Multiple Simulations with Static Behavior (MSSB). For example, the performance of a building with static behavior can be estimated using a BPS model. If the shading includes four scenarios that depend on the characteristics of each season, the CABE performance related to seasonal behavior can be estimated by the sum of the outcomes of four distinct BPS models that are simulated independently for each season (Loonen et al., 2011).

In this way, more short-term behavior (monthly, daily, weekly, and hourly) can be represented using multiple simulations available from distinct BPS models (MSSB strategy). Although the best way to capture CABE behavior frequency is to use the same number of CABE states as the frequency, fewer CABE states can also capture the behavior by assigning them multiple times. For example, 10 CABE states can represent the behavior pattern every hour during an entire year, assuming that each state can be assigned multiple times. Thus, the MSSB strategy relies upon the resolution of behavior frequency and the number of CABE states in the control strategy.

Table 6. MSSB Strategies for CABE behavior representation in BPSs

Behavior frequency	The number of CABE states	The number of BPS models and simulation periods
Static	1	BPS model 1 (1 yr)
Seasonal	4	1 (spring) + 2 (summer) + 3 (fall) + 4 (winter)
Monthly	12	1 (Jan) + 2 (Feb) + 3 (Mar) + • • • • • • • + 12 (Dec)
Daily	365	1 (Jan 1) + 2 (Jan 2) + 3 (Jan 3) + • • • • • • + 365 (Dec 31)

More precisely, optimum CABE control scenarios can be defined by selecting the best outcomes every hour from multiple BPS models (Kim et al., 2015; Vlachokostas and Madamopoulos, 2016). Figure 8 illustrates an example of an optimum CABE scenario during a single day (8:00am to 6:00pm) with an hourly time-scale. If a CABE contains five different geometric states, each can be assigned to five different BPS models as static shading scenarios. Then, each time the best outcome among the five BPS models is selected, that becomes the optimum CABE scenario (see Figure 8).

Based on this approach, Kim et al. (2015) produced multiple BPS models with solar incidence angle-based scenarios using a BIM-based parametric model and estimated CABE performances. Similarly, Vlachokostas and Madamopoulos (2016) evaluated CABE performance using multiple simulations with modified weather data sets that pre-calculated the impact of each shading scenario on the amount of incoming solar radiation. Lee et al. (2016) developed a calculation method for evaluating and delivering CABE performance and operation scenarios based on solar heat gain and lighting energy, with key variables such as fraction unshaded, obstruction index, and exterior solar attenuation coefficient. In this research, the optimal performance scenario was determined by selecting the best outcome each hour from the multiple BPS models.

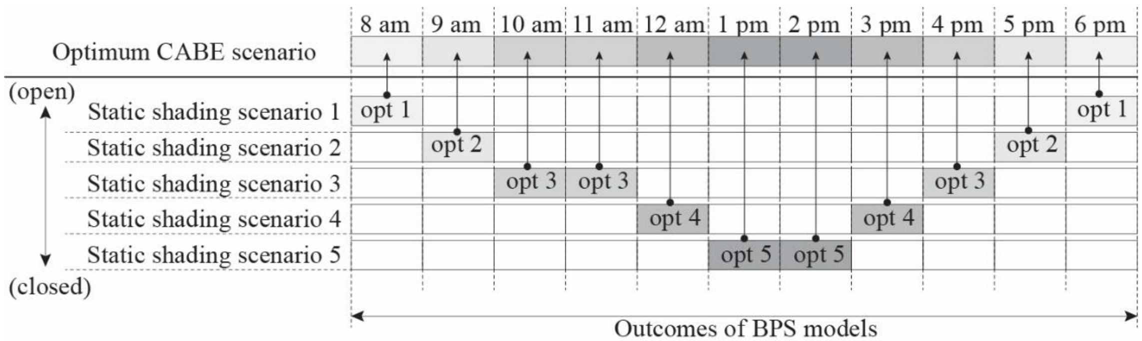


Figure 8. Example of an optimum CABE scenario from the outcomes of the MSSB.

Although this approach represents CABE behavior, certain limitations remain. Using MSSB approach requires additional processes that include the pre-calculation of static models and selection of outcomes, resulting in difficulties with design integration and optimization. This may work well in long-term analyses such as those addressing seasonal behaviors. However, when short-term performance (e.g., hourly performance outcomes) is used to select outcomes, there could be a decrease in accuracy due to the feedback algorithm in BPS tools. The outcomes of load calculations at specific time steps are used for subsequent time steps (Crawley et al., 2001b). Thus, when multiple BPS models are used, there are differences in surface and construction node temperatures at the start of each simulation run, and the effects of transient thermal energy storage cannot be addressed (Erickson, 2013; Loonen et al., 2017).

To overcome these limitations, Kim et al. (2016) used a modified weather data set to simulate CABE performance; the amounts of direct beam and diffuse radiation that reached a window surface via the CABE system were considered for the modification. The modification process included the impact of the CABE scenario on solar radiation, so the MSSB approach was not required. However, this method was available for evaluating the CABE's performance only at one orientation because the modified weather data set contained the amount of incoming solar radiation from only that orientation. In other words, the performance of a CABE system installed on multiple windows and with different orientations in a single thermal zone could not be calculated.

In summary, the limitations of existing performance evaluation methods with complex geometries are listed below:

- Pre- or post-processes are required to simulate multiple BPS models and select the outcomes.
- The use of multiple BPS model increases errors in the outcomes, due to the discontinuous calculation of the effects of transient heat transfer and energy storage effects.

It is important to note that this section has only reviewed the representations of CABE behavior that consider changes in geometric states in BPS models. Changes in material properties across time were not addressed in this review.

2.5. Summary of the CABE-Related Research Agenda

This chapter introduced a research agenda addressing performance-driven CABE designs, following the sequential procedure BPS employs when considering CABE technology: 1) environmental factors, 2) CABE behavior control algorithms, and 3) BPS methods for CABE analysis.

In terms of the environmental factors, various elements and their evaluation indexes were discussed for CABE operation. Ideally, real-time interactions between the sensing of the environment and actuation of CABE aspects represents the best option for both performance and comfort. Also, it is necessary to integrate multiple stimuli for CABE operation. Solar radiation and daylighting are the most commonly used factors in CABE operation. Most of the evaluation indexes for each of these factors were developed independently, focusing on static shading. In this regard, the research agenda for CABE technology related to environmental factors can be summarized as follows:

- Integration with other external and occupant-oriented factors is required for searches seeking superior alternatives.
- The development of a totally integrated and dynamic evaluation matrix is needed to increase the reliability and robustness of CABE designs.

The most important issue for CABE design is how to control the system's behavior to produce optimum solutions. In this chapter, various CABE control algorithms and advanced applications using smart materials were reviewed with associated environmental factors and their thresholds. Also, a direction of research on CABE control algorithms was discussed, along with the related decision-making process. Most research has considered CABE control strategies to either be binary (open or closed) or to have multiple states of openness with linear regression. In this sense, the research agenda for the CABE control algorithm can be summarized as follows:

- The development of a non-linear algorithm determining the openness of a CABE in response to certain environmental factors, producing better CABE operation strategies.
- Well-informed control strategies and information integrated into the development of smart materials and their application in CABE systems.
- Integration with decision-making methods such as optimization and statistical approaches, helping to produce optimum control strategies that address more complex problems such as the consideration of multiple environmental factors and occupant behavior.

Finally, with regards to CABE performance evaluations, this work discussed limitations to the current BPS tools and main challenges of the existing methods. Since current tools do not support the evaluation of CABEs with complex geometries, most studies have used distinct BPS models that contain static shading, and conducted a data sorting process to select optimum outcomes each hour from the multiple simulations. The MSSB approach relies upon behavior frequency and the degree of the CABE state; it also increases inaccuracy in the outcomes and makes design integration difficult. Thus, more research is needed on CABE performance evaluation algorithms that use a single BPS model to represent CABE behavior. In the next chapter, a new algorithm for evaluating CABE performance is introduced by integrating parametric modeling technology.

CHAPTER III

A MODEL FOR EVALUATING AND OPTIMIZING CABE PERFORMANCE

3.1. Overview

The main limitation on the existing methods of conducting CABE performance evaluations is the need to use multiple BPS models. This results in inaccurate performance outcomes and difficulties in testing the various CABE control strategies. This study has focused on the development of a new algorithm to represent CABE behavior that uses a single BPS model called Parametric Behavior Maps (PBM). The use of the PBM for CABE evaluations enables the generation of various CABE behavior scenarios and simulations of their performance. These serve as a means of overcoming the limitations described Chapter 2.

In this chapter, the new algorithm and its validation strategy are described. Section *3.2 Parametric Behavior Maps (PBM) for Evaluating CABE Performance* offers details about the new algorithm's development by representing how it integrates BPSs and parametric modeling methods into CABE performance evaluation. Section *3.3 Validation Strategy* introduces an outline of the validation plan and the reference BPS model used for testing in this research. Section *3.4 Summary* summaries the overall workflows of the PBM and its benefits.

3.2. Parametric Behavior Maps (PBM) for Evaluating CABE Performance

This section introduces the overall workflow of PBM for evaluating CABE performance and optimization. The PBM method consists of three major steps: 1) development of a CABE behavior control strategy (Step 1: CABE Behavior Control), 2) generation of the HBOO scenarios used in the BPS model with CABE technology (Step 2: CABE Behavior Generation), and 3) simulation of the CABE's performance with an assigned behavior scenario (Step 3: Scheduled Behavior Simulation). The PBM method can be implemented along with multi-objective optimization techniques to find the optimum CABE performance set and behavior scenarios that can help designers make better decisions (Step 4: CABE Performance Optimization). Figure 9 illustrates the overall workflow of the PBM method and its implementation in the optimization process. The algorithm was developed based on the parametric modeling environment. A detailed description of each step is offered in the following sections.

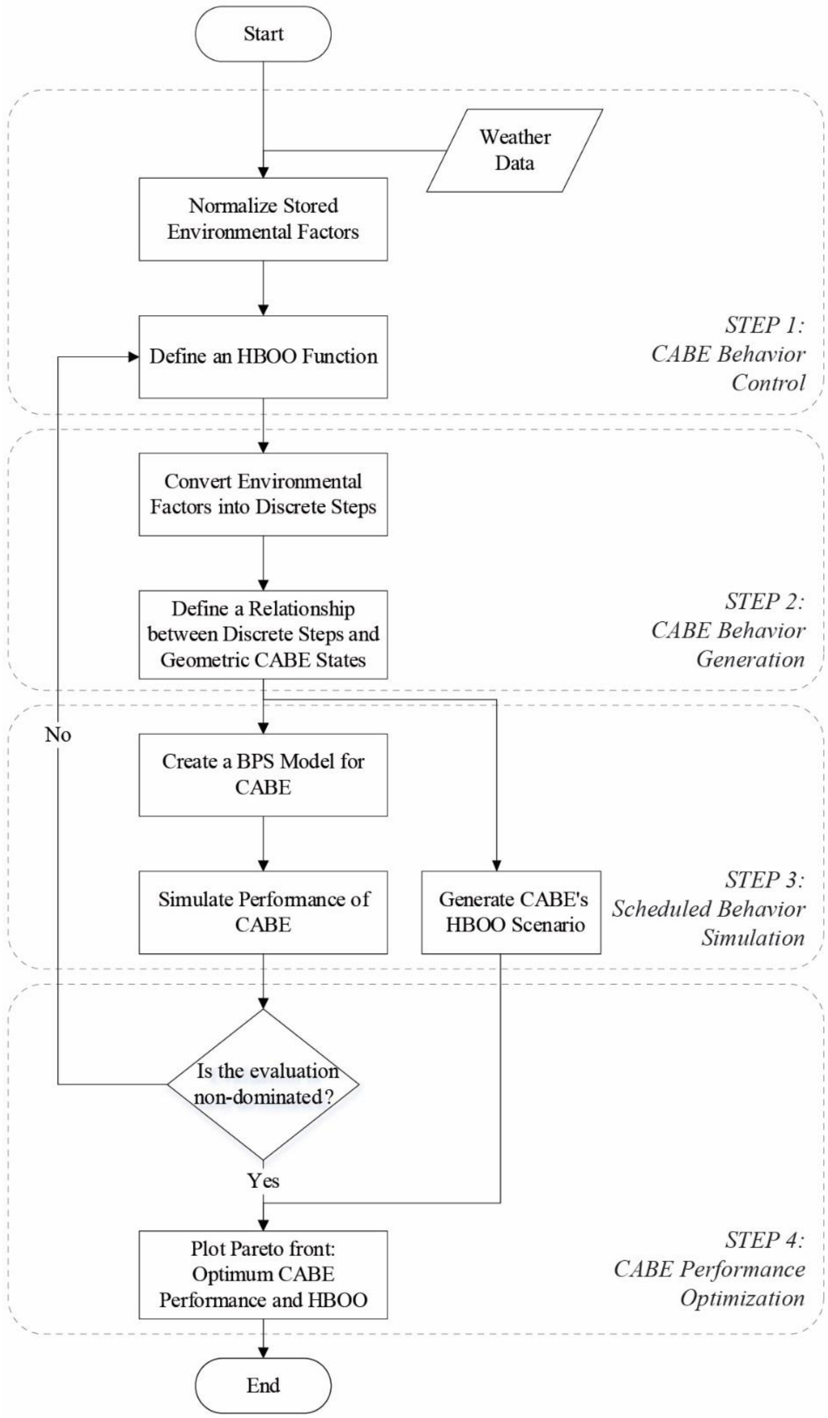


Figure 9. Overall workflow of the PBM for CABE performance evaluation and optimization.

3.2.1. CABE Behavior Control (Step 1)

As illustrated in Figure 9, the first step was to develop a CABE control system by integrating the environmental factors selected from the Typical Meteorological Year (TMY) weather data.

3.2.1.1. Normalization of Environmental Factors

A TMY weather dataset contains hourly meteorological values that represent long-term (30 years) weather conditions at a specific location; the values include various elements such as solar radiation, dry bulb temperature, relative humidity, and wind speed and direction. There were three generations of TMY weather data obtained from the 1952–1975 SOLMET/ERSATZ database (TMY), the 1961–1990 National Solar Radiation Database (NSRDB) (TMY2), and the 1976–1990 and 1991–2005 NSRDB (TMY3). The TMY3 datasets, comprised of data from 1,020 locations throughout the United States, are available for download from the National Renewable Energy Laboratory (Wilcox and Marion, 2008). This research used TMY3 weather data to define the environmental factors and simulate CABE performance.

TMY data can be used directly for a generation of environmental factors when original weather conditions of the surroundings, such as temperature and humidity, are used as a trigger for CABE operation. A converting process is required when the environmental factors are integrated with the building and surroundings. For example, in Figure 10 the amount of solar radiation on surfaces A and B at a specific time are different due to their different orientations (south and east). Also, the radiation patterns for the entire year are presented differently along the sun's path. Solar radiation in the TMY3 data is measured on a horizontal surface; it cannot directly be used as a trigger for CABE operation unless the CABE is installed on a flat roof. Thus, a converting process via simulation or calculation is needed to deliver the actual amount of solar radiation on each surface that could produce different CABE behavior scenarios. Similarly, if other environmental factors such as daylighting, wind, and thermal and visual comfort are used, the converting process from the original TMY3 data to the particular factors should be conducted based on their index in order to accurately respond to changes in the environment.

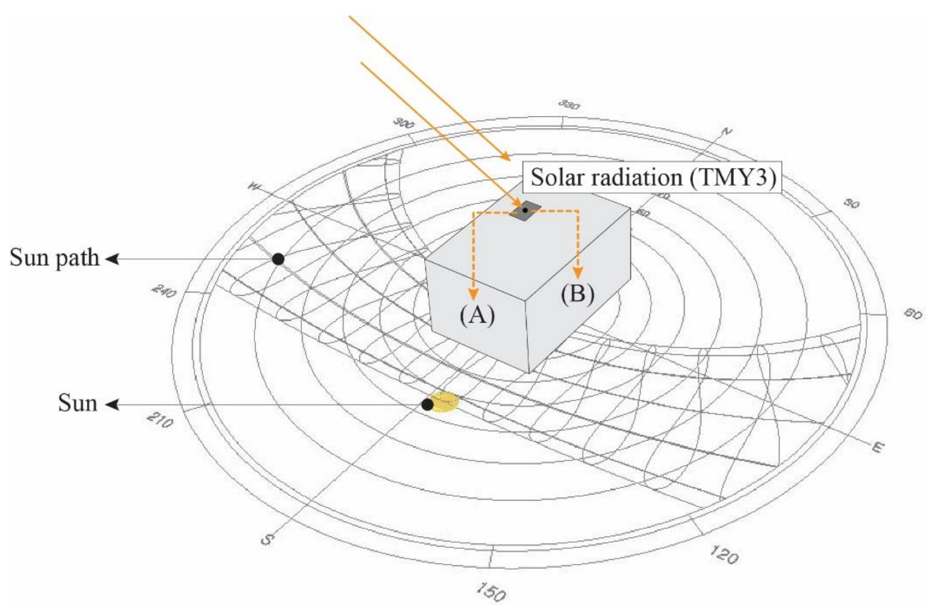


Figure 10. Example of converting solar radiation data from the TMY3 dataset to each surface (south and east).

Although various environmental factors were discussed in Chapter 2, this research used solar radiation as the environmental factor to define CABE behavior scenarios. Other variables can be integrated into the new algorithm, but they are not discussed in this dissertation. The annual solar radiation data contained 8,760 hourly values; they represented the environmental conditions for each hour allowed to define the HBOO scenario for the CABE. After determining the amount of solar radiation reaching the testing surface, its domain was normalized from 0 to 1. The normalization process was designed to easily integrate the environmental factors into the CABE behavior control system, regardless of their indexes or units.

3.2.1.2. CABE Behavior Control System

Although a CABE control system integrated with an HBOO function was described in Step 1 of the workflow outlined in Figure 9, that system was directly related to the CABE behavior generation process (Step 2). Thus, to make it easier to understand, a detailed description of the control system is described in Section *3.2.2.3. Development of a Function-based Behavior Control System*.

3.2.2. CABE Behavior Generation (Step 2)

The second step, illustrated in Figure 9, was to generate a CABE behavior scenario based on the variables derived in Step 1. The output could then be used to represent CABE behavior in the BPS model.

3.2.2.1. Creation of a Discrete Model of Environmental Factors

The set of normalized solar radiation values obtained from Step 1 was grouped into a number of categories specified by the behavior types of the CABE's controls (binary or multiple). CABE controls with binary states included two categories, while CABE controls with multiple states included several categories, based on the number of geometric states in the CABE operation scenario (see Figure 11A). In Figure 11A, five categories (b1 to b5) are presented as an example of CABE controls with multiple states; this means that five geometric CABE states were considered when devising the CABE's operation schedule. Also, the relationship between the level of openness of the CABE and category of normalized solar radiation values represented the CABE's various behavior scenarios. The left and right graphs show the relationship between the level of openness and the binary and multiple states, respectively (see Figure 11B).

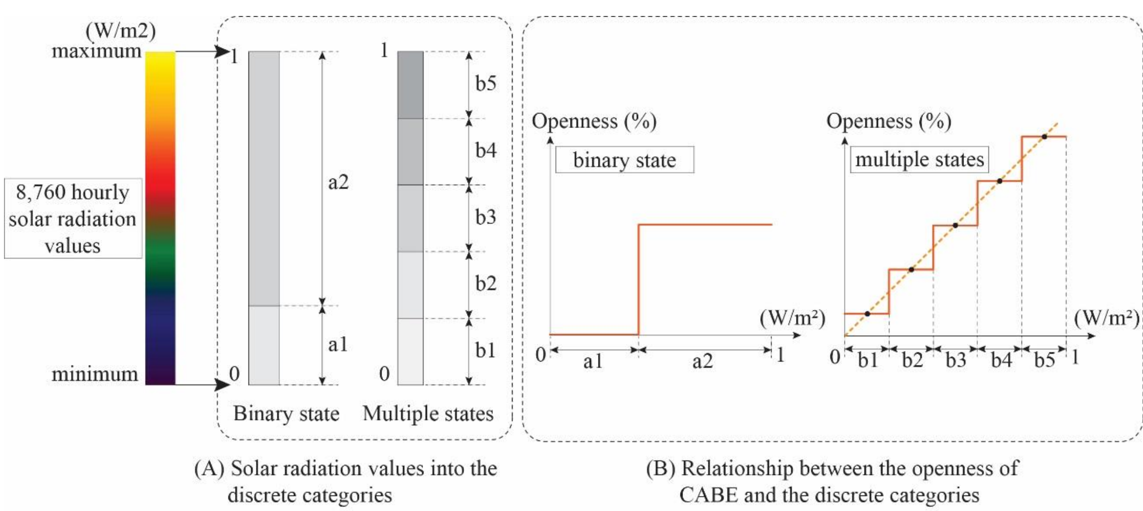


Figure 11. Example of converting the environmental factor into discrete categories.

3.2.2.2. Creation of the HBOO Scenario

Continuing with the example presented in Step 1, five categories (b1, b2, b3, b4, and b5) were assigned to the static geometric CABE states (c1, c2, c3, c4, and c5); each state represented a specific level of openness of the CABE (see Figure 12A). In other words, 8,760 solar radiation values were distributed among five different geometric states, based on the discrete categories. The goal was to assign geometric CABE states to specific times. The CABE operation scenarios were represented as combinations of static geometric states over time, based on the value of the solar radiation for every hour. Eventually, a series of static geometric states over time was able to represent the HBOO of the CABE (see Figure 12B).

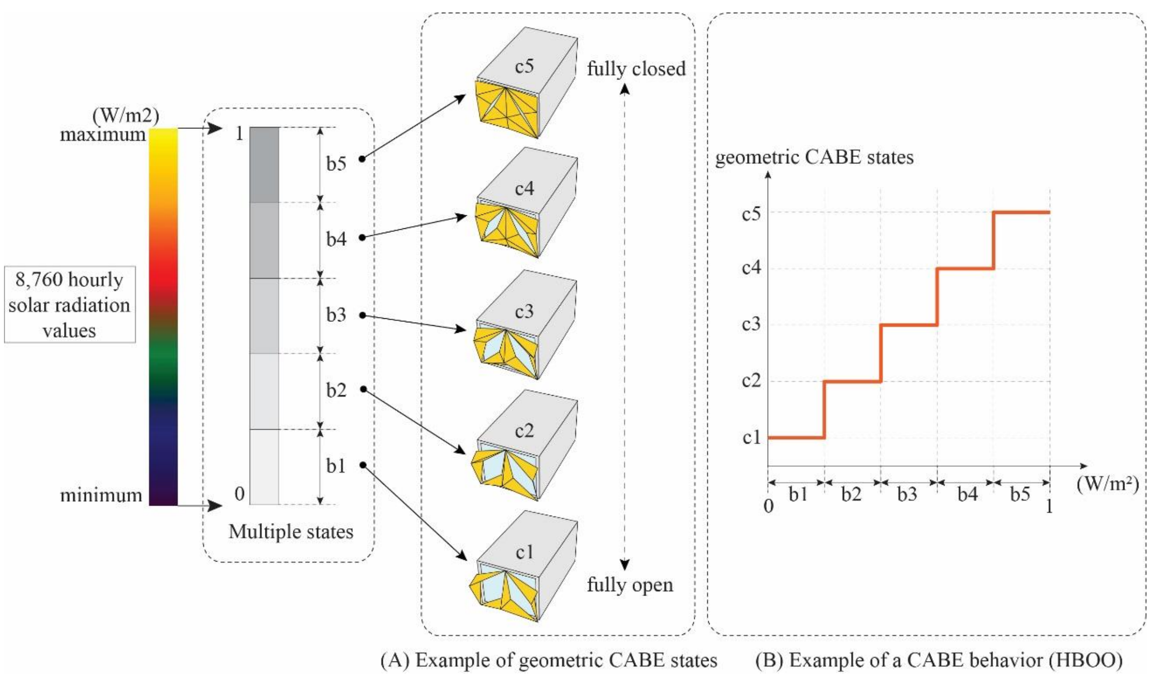


Figure 12. Example of the generation of an HBOO for each CABE state.

3.2.2.3. Development of a Function-based Behavior Control System

In terms of the multiple states illustrated in Figure 12, the normalized radiation values were evenly divided into five categories; this produced a CABE behavior by following a linear regression between the geometric CABE state and the category of solar radiation. This meant that the CABE behavior scenario relied upon the division pattern of the categories. If category b1 accounted for a large portion of the domain of the normalized values, a different CABE behavior was produced by following a different regression (see Figure 13). In this way, various CABE behaviors (either linear or nonlinear) could be produced by controlling the portion of the five categories. However, it is important to note that the use of a large number of variables could result in optimization failure or inaccurate solutions when conducting the optimization process. The variables in this algorithm were the discrete categories of normalized environmental factors. A large number of categories produced more sensitive CABE behavior and resulted in an increase in reliability. Simultaneously, however, this also increased computational cost and the likelihood of failure of the optimization process.

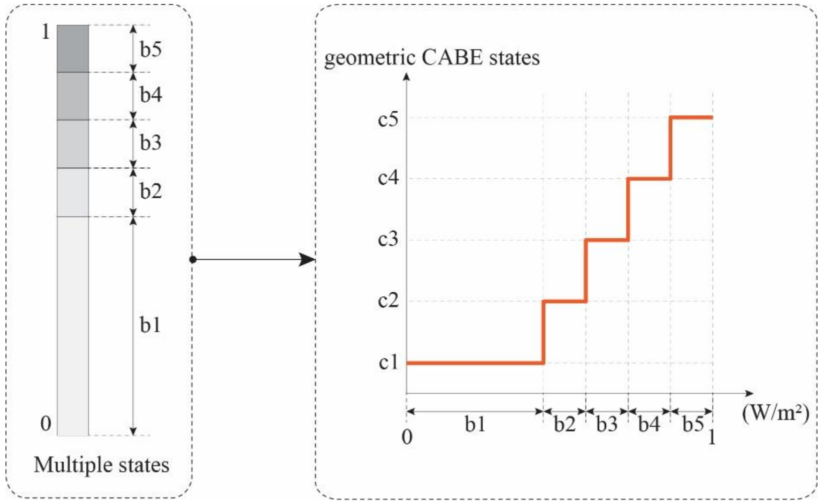


Figure 13. Example of the generation of different HBOO scenarios using discrete categories.

To control the variables more efficiently, a Function-based Behavior Control System (FBCS) was developed by integrating numerical models (linear or non-linear functions) that changed the distribution pattern of the solar radiation values (see Figure 14A). For example, linear Equation (1) could be used during the normalization process of the domain of solar radiation values; the distribution patterns could be changed based on the variables in Equation (1), as illustrated in the left graph in Figure 14B.

$$f(x) = ax + b \tag{1}$$

where:

f(x) = the new normalized solar radiation values for HBOO generation

x = the normalized solar radiation values on a window

a = variable 1

b = variable 2

If a linear function was not used, changes in the apportioning of the five discrete categories (see Figure 13) served as the variables. Conversely, the use of a linear function that contained two variables enabled the solar radiation values to be distributed to the fixed categories (see Figure 14). Thus, regardless of the number of discrete categories (geometric CABE states), the CABE's behavior optimization can be processed using only two variables if the designer considers the CABE behavior with a linear regression between the environmental factors and the CABE's HBOO. In this way, various non-linear functions can be applied to search larger spaces for optimum CABE behavior scenarios (see the right graph in Figure 14B). Also, the use of more complex or multiple functions could represent discontinuous behaviors that might produce better performance outcomes. Although the use of the FBCS reduces the search space, it significantly increases the efficiency of the optimization algorithm, especially when a large number of geometric CABE states are applied.

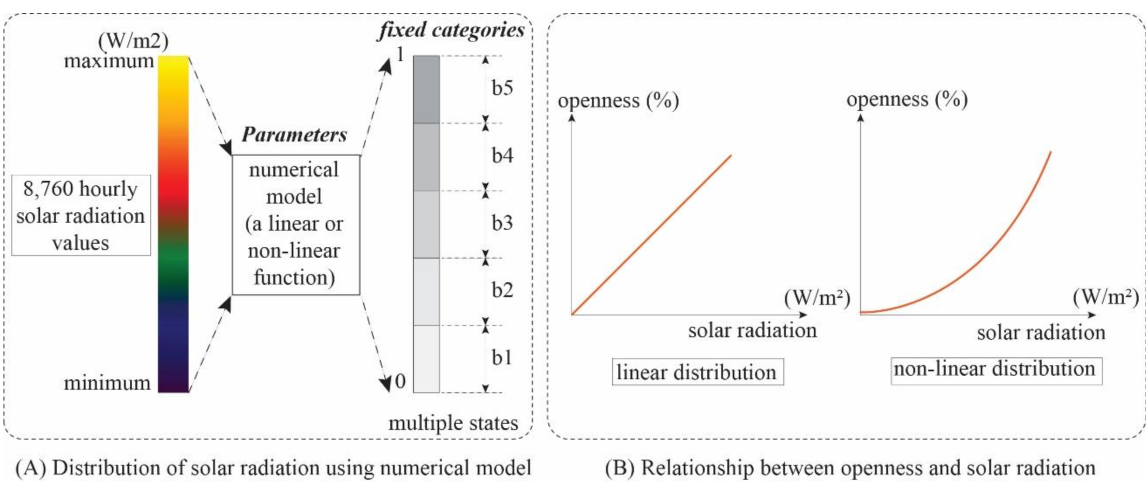


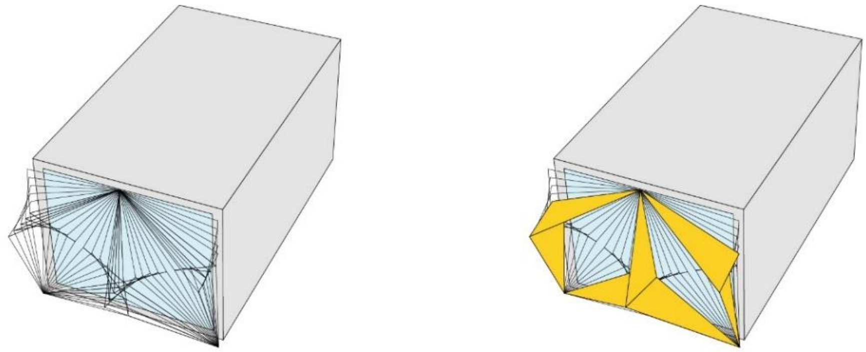
Figure 14. Function-based Behavior Control System with numerical model.

3.2.3. Scheduled Behavior Simulation (Step 3)

The third step, illustrated in Figure 9, was to create a BPS model for the CABE that could represent the HBOO and simulate the energy and daylighting performance.

3.2.3.1. Overview of the Creation of a BPS for CABE

In BPS models, static shading surfaces detached from the building model can be developed along with their Schedule of Solar Transmittance (SST), in order to represent shading, the surroundings, trees, and hills. A 3D complex geometry can be created as long as the shape consists of flat polygonal surfaces (DOE, 2010). In this research, all of the CABE's geometric states were included in a single BPS model as shading surfaces detached from the building model. These were categorized based on the geometric states of the particular CABE scenario (c1, c2, c3, c4, and c5 in Figure 12A) controlled by the SST representing the HBOO of the CABE. For example, in Figure 15A, all of the CABE's geometric states were included in the BPS model as shading, with the SST set to 100% at all times. The intention was that there would be no shading effect in terms of the amount of incoming solar radiation. In Figure 15B, the SST in the c1 state was set with a 0% level of solar transmittance; the rest of the CABE states (c2, c3, c4, and c5) were scheduled to have 100% solar transmittance at all times. In other words, among all of the CABE states, only c1 was considered as static shading.



(A) 100% solar transmittance: all CABE states

(B) 100% opaqueness: c1
100% solar transmittance: c2, c3, c4, and c5

Figure 15. An example of a CABE BPS model with solar transmittance.

3.2.3.2. Representation of CABE Behavior in the BPS Model

Change in solar transmittance schedule enables the BPS model to represent various seasonal, monthly, and daily CABE behavior scenarios. Figure 16 illustrates an example of the BPS process during working hours (8:00am to 6:00pm) in a single day, illustrating how CABE behavior can be represented in a BPS model by integrating a set of static shadings with their SST. Based on the number of discrete categories, the same number of SSTs were created. In this example, five SSTs (SST1 to SST5) were created to correspond with the five discrete categories of solar radiation values (b1 to b5). Each SST was assigned to a geometric CABE state (c1 to c5) to represent hourly-based SST values using a binary pattern, 0% or 100% solar transmittance; the five hourly-based SSTs were defined by the amount of solar radiation received each hour. Thus, in each hour one geometric CABE state became opaque, responding to the amount of incoming solar radiation on the surface. For example, the c1 state was scheduled to be opaque at 8:00am and 6:00pm, when the solar radiation was category b1. This meant that the c1 state functioned as shading only at 8:00am and 6:00pm based on SST1; it was not intended to be shading during the rest of the time (see Figure 16). In this way, the HBOO could be mapped on a BPS model in a way that enabled it to simulate the CABE performance. The five SSTs could be combined by selecting 0% of the solar transmittance at each hour; this would then comprise an HBOO for the CABE system. The behavior scenarios were dependent upon the discrete categories of hours with particular solar radiation thresholds. Thus, the algorithm provided a parametric simulation of a CABE's performance with complex geometry using a BPS model.

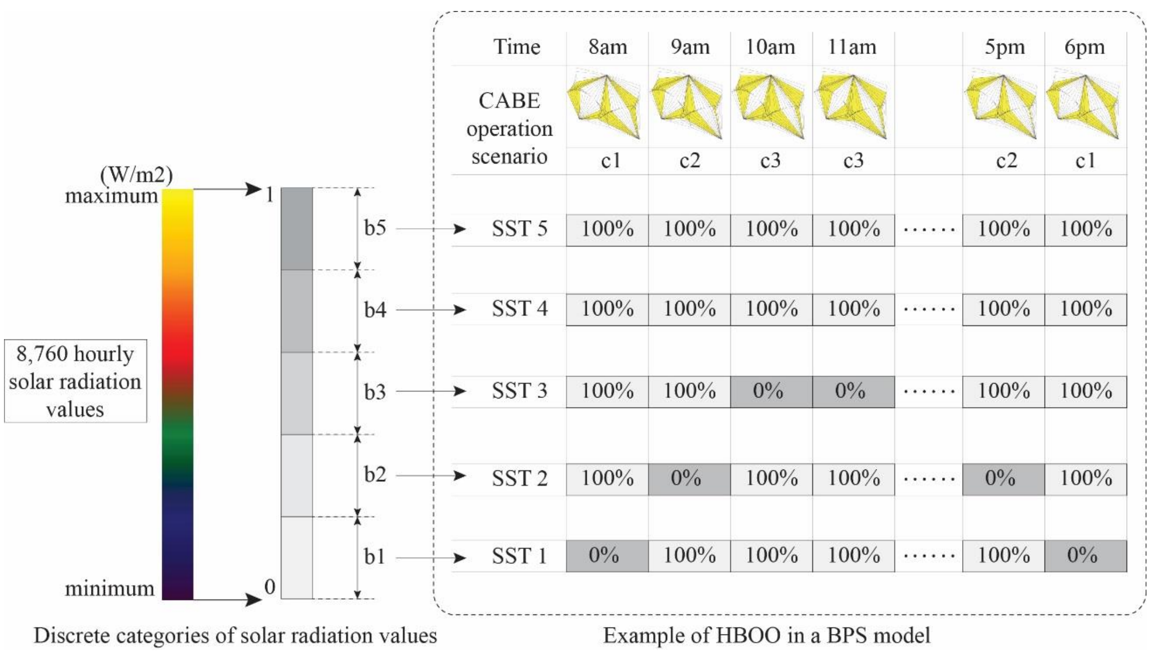


Figure 16. Example of CABE behavior mapped onto a BPS model.

There were some assumptions made in the shading transmittance calculations used in this algorithm (DOE, 2010):

- The same transmittance properties were applied to both sides of the shading.
- There was no inter-reflection between the shadings or between the shadings and buildings.
- In terms of radiation transmittance, beam and diffuse radiation were considered to be the same with respect to the shading state.
- Beam radiation was transmitted to the shading surface without a change in direction.
- In terms of the daylighting calculations, visible transmittance of the shading was considered to be the same as the solar transmittance.
- Regardless of the transmittance values, the shading device was opaque to long-wave radiation.

3.2.4. CABE Performance Optimization (Step 4)

The CABE performance outcomes obtained from the PBM method (Steps 1 to 3) could then be integrated with the multi-objective optimization process. For an effective optimization process, well-defined variables and constraints are necessary. As described in previous sections, the PBM method was able to produce an HBOO scenario based on a selected function; creating different types of functions served as variables in the optimization process, as shown in Equation (1). The integration of the PBM process and EMO produced new generations of CABE performances and HBOO scenarios; EMO determined whether the CABE performance met the objectives and produced a set of Pareto front solutions that included the optimum CABE performance and HBOO. By following the overall workflow, users can compare multiple CABE alternatives and make a CABE-based design decision based on their performance preference among the various Pareto front solutions.

3.3. Validation Strategy

This section introduces the validation strategy for the new algorithm and hypotheses described in Chapter 1. Detailed information about the reference building model is also provided, along with the input parameters for the BPS model. Also, the comparative studies and optimization frameworks are summarized, as well as the assumptions made for the testing.

3.3.1. Climate Conditions for Testing

The International Energy Code Council and ASHRAE have adopted the standard climate zones developed by DOE for residential and commercial building applications; eight thermal zones (1 to 8) have been created to represent the various climate conditions in the US. Most zones contain three sub-categories, reflecting moist (A), dry (B), and marine (C) regions (Briggs et al., 2003).

In this research, Houston, Texas, a hot and humid (2A) climate, was selected as a location in the BPS model in order to test its validity. In Houston, the number of comfortable hours can be increased by up to 21 percent through the installation of appropriate static shading devices. This means that control of the incoming solar radiation is one of the most important sustainable design strategies (Liggett and Milne, 2014), and that implies that the use of CABE systems could have a significant role in reducing energy demands in Houston.

3.3.2. Reference Building Model

In this research, a small office building was employed for the reference model. As illustrated in Figure 17, a single thermal zone in a closed office space with a south-facing orientation was developed; its dimensions were 3.6m × 6m × 3m (length × width × height), and there was a window on the south wall with an 80% window-to-wall ratio (WWR). To measure the simulated daylighting level, a total of 60 sensors were located in the model at a 0.8m height above the ground; the dimensions of each grid were 0.6m × 0.6m (length × width) (USGBC, 2013). Two dimming control sensors were located in the middle of the zone; the target daylighting level was 375lux, meaning that artificial light was turned on when the illuminance levels at the sensors fell under 375lux.

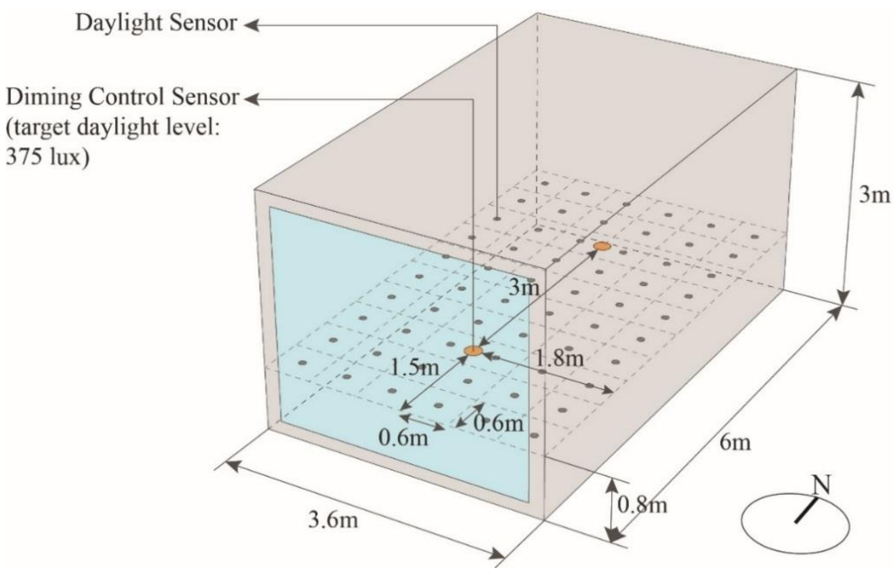


Figure 17. Dimensions and daylighting sensor locations in the reference building model.

The DOE Commercial Reference Building Models of the National Building Stock are widely used as reference models (Deru et al., 2011) for the input parameters of BPS models. DOE provides reference building types that represent commercial and high-rise apartment buildings across all climate zones in the US. In this research, input information for the BPS model, such as internal loads and schedules, was developed by following the small office building type in a 2A climate zone (Houston) that complies with ANSI/ASHRAE/IES Standard 90.1-2013. Table 7 describes the input information of the reference BPS model used in this research; the schedules of the input values are described in the small office hourly operation schedules in the reference models (Deru et al., 2011).

Table 7. Input Values in the Reference Building Model

Category	BPS input parameters	Input value
Building	Climate zone / Location	2A / Houston, TX, US
	Orientation	South
	Geometry	3.6m × 6m × 3m (length × width × height)
	WWR (South) (%)	80
Material (daylighting)	Visible reflectance (%)	50 (interior wall) 20 (floor) 30 (celling and south wall)
Construction	Exterior wall (South) (W/m^2-K)	U = 0.505
	Other walls, floor, and roof	Adiabatic
	Window (W/m^2-K)	U = 0.6 (double pane glass, SHGC = 0.25)
Internal Loads	People (person/m^2)	0.060284
	Light (W/m^2)	8.826406542
	Electric equipment (W/m^2)	6.78
HVAC	Ideal Loads Air System	Thermostat Setting (cooling /heating) Occupied: 75° / 70° Unoccupied: 85° / 60°

3.3.3. Comparative Studies and Optimization Frameworks

In this research, the following comparative studies and optimization frameworks were conducted in order to validate the algorithm and hypotheses:

- Two test cases were conducted based on CABE behavior scenarios to validate the PBM method developed in this study. First, several CABE behaviors were generated using the PBM to represent various static shading designs; the outcomes were compared with the results obtained from the BPS model with static shading, which served as a reference model. Second, a dynamic CABE behavior was included to determine the reliability and robustness of the algorithm; the results of the PBM were compared with outcomes using the MSSB approach.

- Optimization studies with the PBM were undertaken to achieve the optimum HBOO scenarios for specific CABE designs, including both linear and non-linear CABE behavior scenarios.

Further development of this new algorithm requires additional investigation and application, including more complex and practical cases. However, this research has focused on developing a performance evaluation method for CABE technology at the foundation stage. Thus, the scope of the testing conducted for this research can be described as follows:

- One environmental factor, solar radiation, was considered to be a trigger for the CABE's operation. Multiple environmental factors were not considered for this research; this type of analysis will be included with uncertainty and sensitivity analyses in future work.
- The simulation period was one month in summer (July) and one month in winter (December). The amount of global solar radiation in Houston is highest and lowest in July and December, respectively.
- All test cases were conducted under the assumption that there was no solar radiation reflected from the exterior surfaces (including CABE surfaces) and

ground, in order to minimize the impact of the material properties of the shading device.

- Although the level of solar transmittance could be controlled in the BPS model, 100% opaqueness was applied in all test cases when a CABE's shading state was activated.
- For the daylighting performance evaluation, a thermal model was used to obtain illuminance values and electric light energy from a diming control system. This allowed for the use of one BPS model and minimized the computational costs. Further integration with dynamic daylighting simulation tools will be conducted in future research.

3.4. Summary

This chapter introduced the workflow of a new algorithm for evaluating CABE performance. The process consisted of three steps: CABE Behavior Control, CABE Behavior Generation, and Scheduled Behavior Simulation. Figure 18 offers a graphical representation of the workflow. The algorithm used one BPS model by mapping the CABE's behavior, based on environmental factors. Also, the development of the FBCS enabled the efficient generation of the optimum CABE behavior scenarios.

The benefit of the algorithm is that it accurately represents the impact of solar radiation, including direct, diffuse, and reflected energy. Also, unlike existing functions in BPS tools, this algorithm represents 3D shading geometry using flat polygonal surfaces, regardless of the shape of the windows.

The next chapter presents the outcomes of the testing for validation of the algorithm and provides evidence supporting the hypothesis of this study.

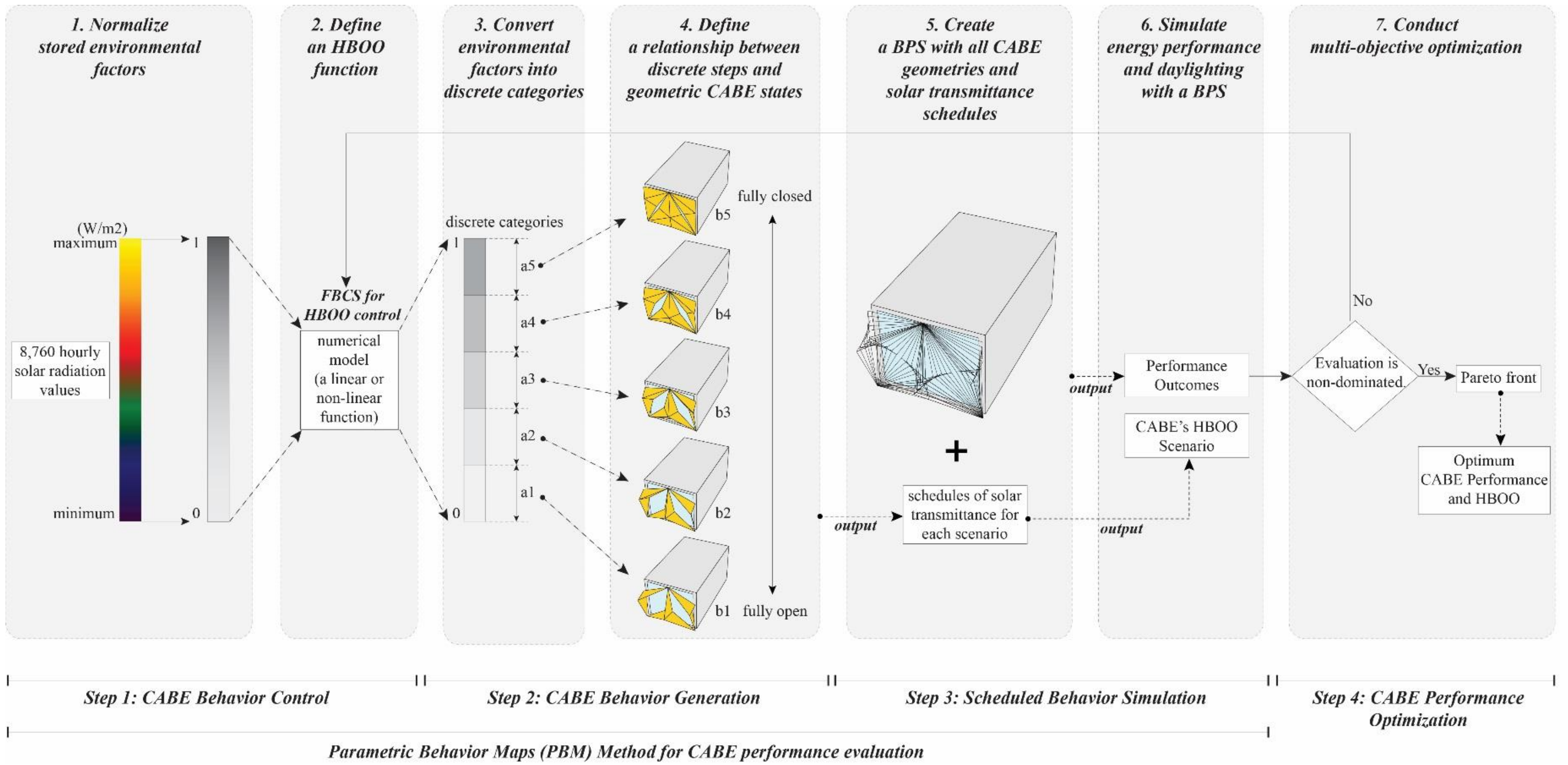


Figure 18. Graphical workflow of the algorithm for CABE performance evaluation.

CHAPTER IV

VALIDATING THE PARAMETRIC BEHAVIOR MAPS (PBM) METHOD IN CABE PERFORMANCE EVALUATIONS

4.1. Overview

This chapter presents the results of test cases performed to validate the use of the PBM employed when using the CABE performance evaluation process described in the previous chapter. Two test cases were conducted that measured two different elements: solar radiation transmitted through a window and indoor air temperature profiles in a thermal zone. Test case 1 determined the amount of solar radiation transmitted through a window with a CABE system to validate the use of the PBM in CABE performance evaluations. Test case 2 measured indoor air temperature profiles to investigate the reliability and robustness of the method as compared to a more traditional process. The results show that the PBM delivered more accurate simulation outcomes than the existing traditional method, which used a combination of the results of separate BPS models run over less than a complete interval of the study; thus, it can widely be applied regardless of a building's orientation and sky conditions.

Section *4.2 Description of the CABE Models* describes two different CABE models and the assumptions employed in the BPS model used in this chapter. Section *4.3 Testing for Validation of the PBM Method (Test case1)* provides evidence that validates the use of the PBM algorithm for CABE performance evaluations. Section *4.4 Robustness Testing of the PBM Method (Test case2)* shows the robustness of the PBM method compared to the MSSB traditionally used in CABE performance evaluations. Section *4.5 Summary* summarizes the results of the comparative studies described in this chapter and discusses future applications and limitations.

4.2. Description of the CABE Models

4.2.1. CABE Model 1

CABE Model 1 consisted of five geometric states, each of which combined one overhang and two vertical fins. The dimensions of each overhang and vertical fins were 3.22m × 0.2m (length × width) and 2.68m × 0.2m (length × width), respectively, which followed the shape of the window (80 percent of WWR) on the south wall. The BPS model included all overhangs and vertical fins; each state was developed with one overhang and two vertical fins. The size of overhangs and fins shrank and grew, ranging from the A1 to A5 states, by changing the schedule of solar transmittance. The maximum length of the CABE was 1m when it was fully extended (see Figure 19). CABE Model 1 transformed in the normal direction of the window to block or gain beam radiation in the summer and winter seasons, respectively. The impact of the transmitted diffuse radiation could be considered regardless of its state.

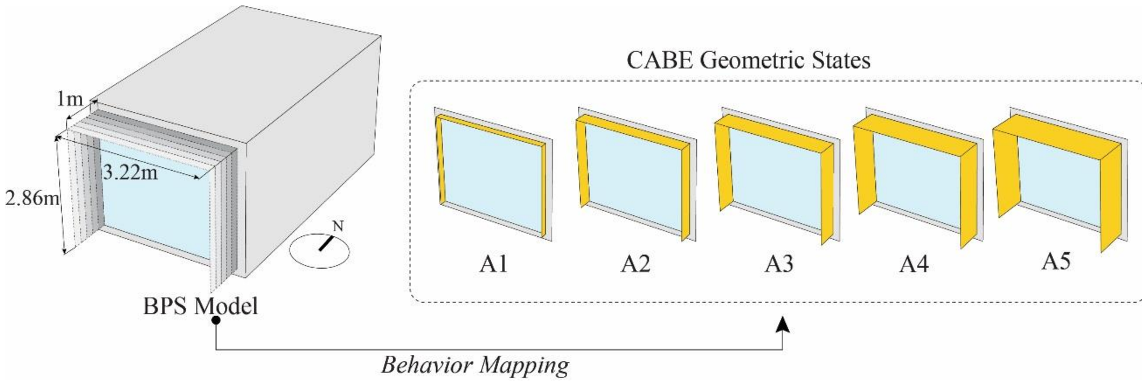


Figure 19. Dimensions and geometric configurations of CABE Model 1.

4.2.2. CABE Model 2

A CABE system designed by Grant Associates and Wilkinson Eyre Architects was installed in the Gardens by the Bay building in Singapore (see Figure 20). It consists of outdoor motorized triangular screens that are two-dimensionally tensioned by a cable system in order to reduce incoming solar radiation and preserve natural light (Serge Ferrari, 2014). Figure 20 illustrates the geometric configuration of this CABE system, as observed from the exterior (see images 1 to 4 in Figure 20) and interior (see images 5 to 7 in Figure 20); its transformation is created by the scaling patterns of the triangular screens.

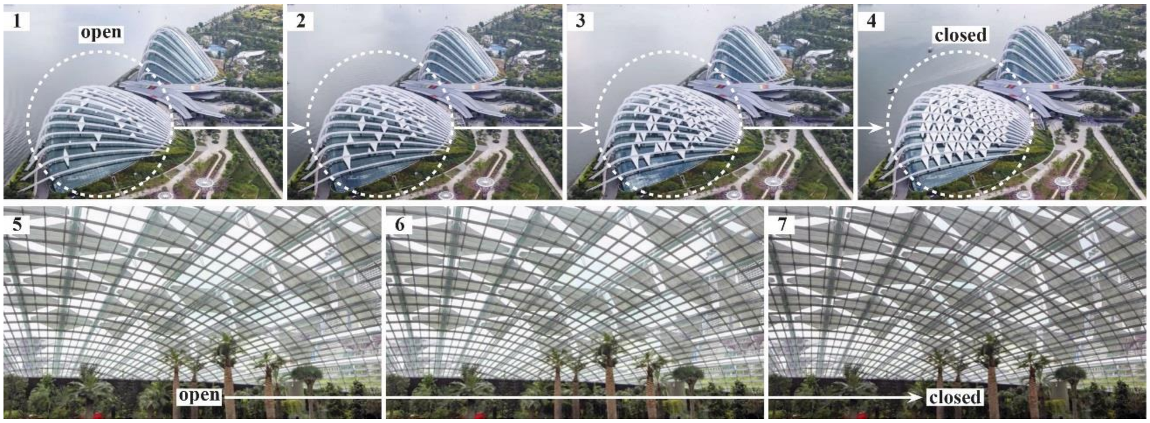


Figure 20. Configuration of the CABE system installed in the Gardens by the Bay building (Serge Ferrari, 2014).

In CABE Model 2, five geometric states (A1 to A5) were developed and located in front of a window on the south wall to describe the CABE system in the Gardens by the Bay building; the distance between the wall and the CABE system was 20cm (see Figure 21). All triangular shadings were included in the BPS model; each shading could be activated by setting one of five schedules of solar transmittance, in order to represent the five geometric CABE states. Unlike CABE Model 1, CABE Model 2 could transform its configuration in a direction parallel with the window; it completely covered the window when the CABE state reached A5.

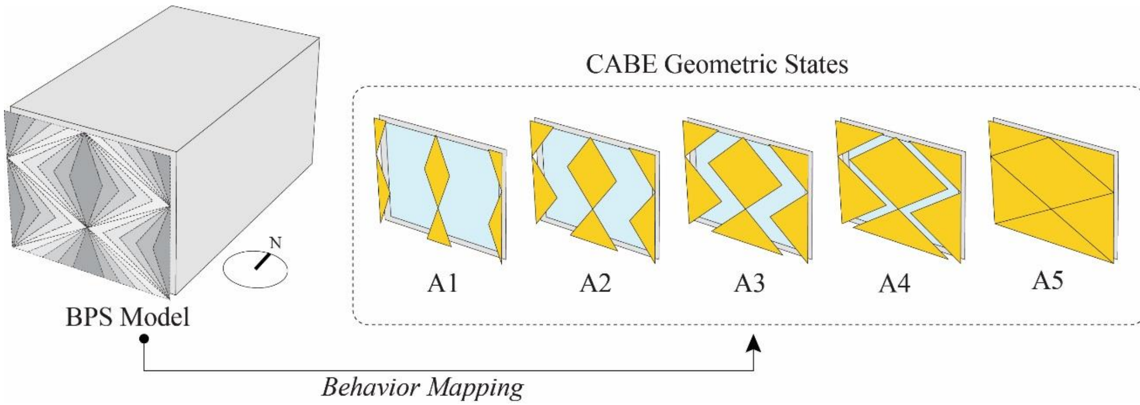


Figure 21. Geometric configurations of CABE Model 2.

4.2.3. Test Case Model Assumptions

All test cases in this chapter employed the following assumptions to investigate the impact of solar radiation on the minimization of other elements.

- The walls, floor, and ceiling were set as adiabatic surfaces, except for the south wall and window. Adiabatic surfaces were used for interior walls that faced zones with the same thermal conditions. This meant that there was no heat transfer though the adiabatic surfaces, which is a typical assumption for interior surfaces. Heat transfer occurred through the south wall and window that faced the outdoor conditions.
- The material properties of the south wall and window followed the reference building model described in Table 7.
- There were no internal loads that could significantly influence the CABE's performance.

- In terms of solar radiation distribution, it was assumed that all beam radiation entering into the zone fell onto the floor; the reflected radiation from the floor depended on the solar radiation absorption of the floor material. All radiation reflected by the floor was uniformly distributed across the interior surfaces and added to the transmitted diffuse radiation.

4.3. Testing for Validation of the PBM Method (Test Case 1)

To validate the reliability of the PBM method, comparative studies were conducted based on each CABE model. EnergyPlus was used to simulate the hourly transmitted solar radiation rate throughout the year for the window with the CABE system; the outcomes were compared based on the CABE scenarios listed in Table 8. The CABE scenarios in this section were developed to represent static shading. More precisely, although the BPS model included all of the CABE states, the CABE system was activated as a static shading using a constant CABE behavior throughout the year. Thus, the outcomes from the CABE system and static shading could be compared to one another to determine their relationship. For example, in CABE Scenario 1 all CABE states were scheduled with 100% solar transmittance throughout the year; this scenario mimicked that of the base model without shading, in accordance with the algorithm of the PBM method. Similarly, the BPS model with static shading (A1) corresponds to CABE Scenario 2, where CABE state A1 was scheduled with 0% solar transmittance throughout the year, and the rest of the states (A2, A3, A4, and A5) were hidden using

100% solar transmittance (see Table 8). In this way, other CABE scenarios could be compared with static shading scenarios to validate the PBM method.

Table 8. List of CABE Scenarios Used to Test CABE Models 1 and 2

	CABE System	Static Shading
CABE Scenario 1	All CABE states: 100% solar transmittance	no shading
CABE Scenario 2	CABE A1 state: opaque	static shading (A1)
CABE Scenario 3	CABE A2 state: opaque	static shading (A2)
CABE Scenario 4	CABE A3 state: opaque	static shading (A3)

The squared correlation was calculated to demonstrate how closely the hourly transmitted solar radiation rates from the CABE scenarios agreed with the data from the static shading scenarios. The scatter plot indicates that the outcomes from the CABE system and static shading were exactly the same as $R^2 = 1$ for both CABE models and all scenarios (see Figures 22 and 23). This correlation supports the notion that the PBM is capable of representing a static shading design, since the outcomes of each of the individual states obtained from the PBM results were similar to the static models. This is evidence supporting the hypothesis that the PBM method can be used to represent the dynamic behaviors of CABE systems when evaluating their energy and daylighting performances.

Although the same CABE behaviors were set for both models based on open to closed patterns (CABE Scenarios 1 to 4), less solar radiation was transmitted in CABE

Model 2 as the CABE scenarios were closed. This means that CABE Model 2 was more sensitive to solar radiation than CABE Model 1, which originated from the geometric transformation patterns (as described in the previous section; see Figures 22 and 23).

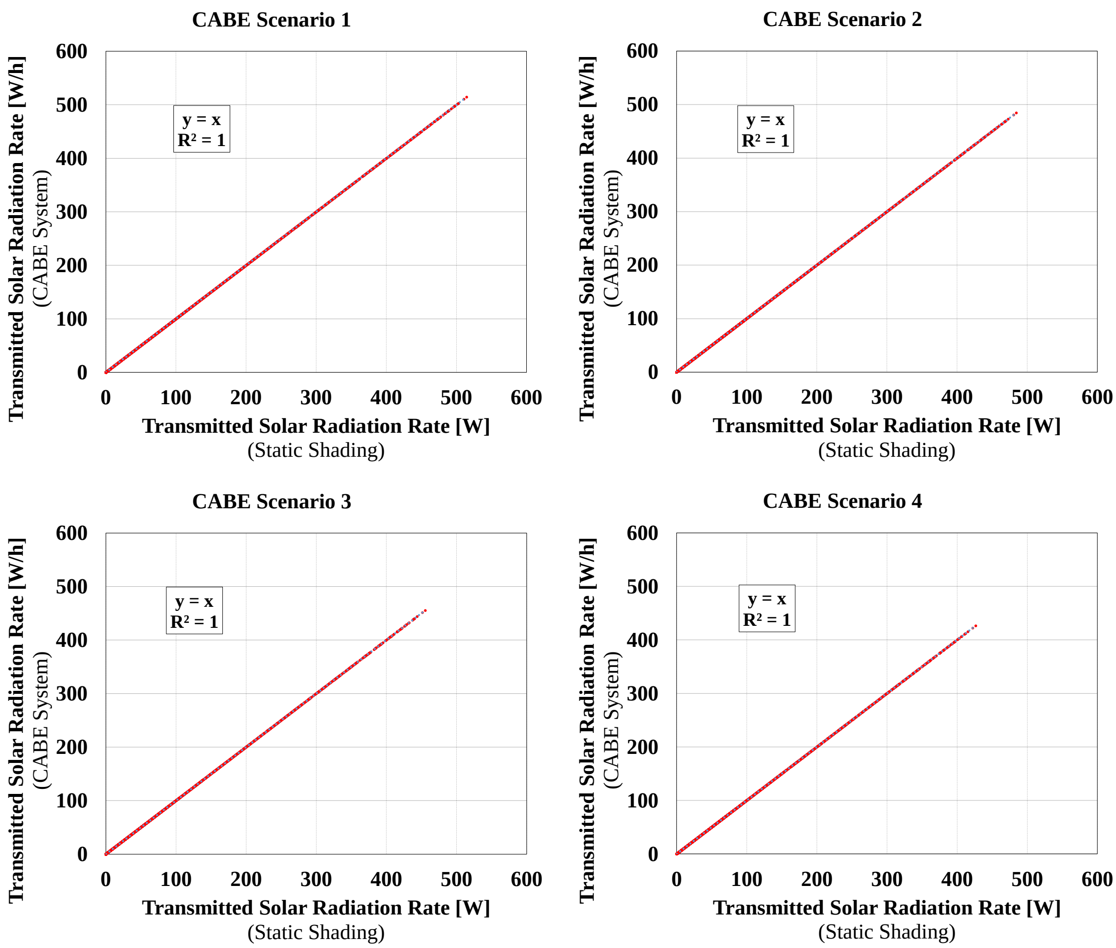


Figure 22. Correlations among the transmitted solar radiation rates for the windows with CABE systems and fixed shading scenarios (CABE Model 1).

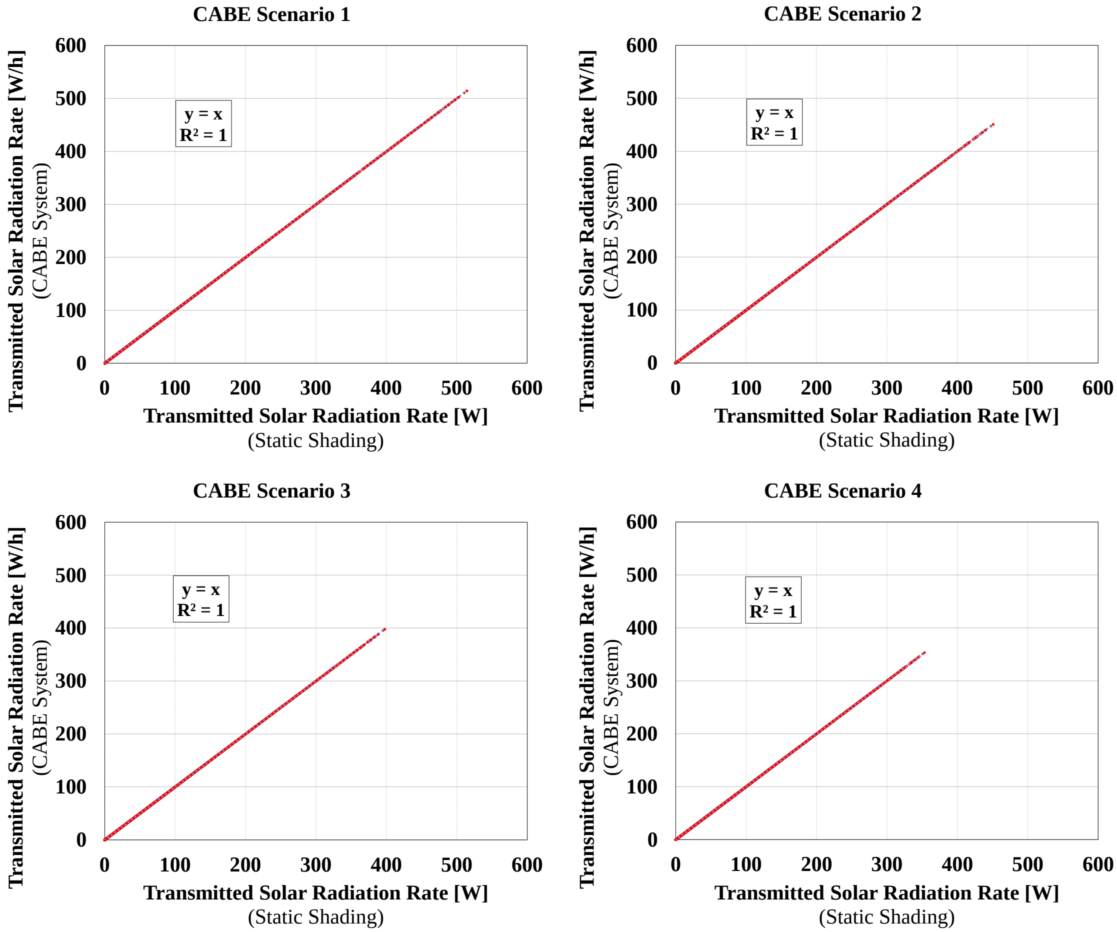


Figure 23. Correlations among the transmitted solar radiation rates for the windows with CABE systems and fixed shading scenarios (CABE Model 2).

4.4. Robustness Testing of the PBM Method (Test Case 2)

In the previous section, CABE behaviors were considered to be constant values representing static shading scenarios, due to limitations in the current simulation tools. In this section, a dynamic CABE behavior scenario for each season (summer and winter) was used to simulate a CABE system's performance using the PBM method. Indoor air temperature was simulated to identify the impact of transmitted solar radiation on the thermal conditions and present the reliability and robustness of the PBM method as compared to the MSSB.

4.4.1. Description of a Linear CABE Behavior

A linear CABE behavior scenario was generated based on the amount of solar radiation reaching a window without shading; this was accomplished by following the process described in Section *3.2.1 Parameterization* in Chapter 3. The solar radiation values reaching the window were simulated; the maximum values were 392.5 W/m^2 and 902.4 W/m^2 in July and December in Houston, Texas. Based on the ranges, 744 hourly solar radiation values for each month were normalized by mapping the maximum value to 1; then, other values were distributed in the range from 0 to 1, based on a linear relationship. The upper graphs in Figures 24 and 25 represent the normalized solar radiation reaching the window in July and December, respectively.

The domain of normalized solar radiation was divided into five categories, based on the number of CABE geometric states described in CABE Models 1 and 2. For example, CABE state A1 was scheduled to be opaque when the normalized solar radiation values ranged from 0 to 0.2 in July. The behaviors for CABE states A2 to A5 were also defined by the same process; A5 was activated five times during the month (744 hours) (see lower graph in Figure 24). This trend was designed to control the CABE states based on the amount of solar radiation reaching the window without shading; as incoming solar radiation was increased, more shadings in the CABE system were activated. Following this process, a second CABE behavior scenario was designed for winter (December), where the CABE states became more open when incoming solar radiation was increased, in order to promote heat gain (see lower graph in Figure 25).

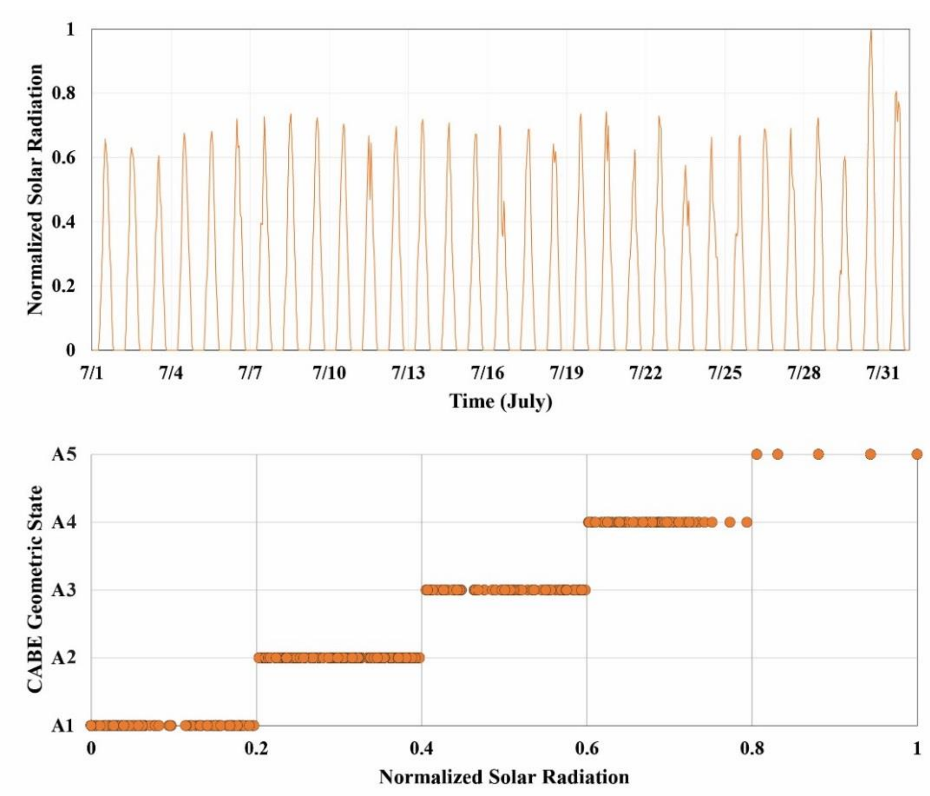


Figure 24. Relationship between the normalized solar radiation values and CABE geometric states in summer (July).

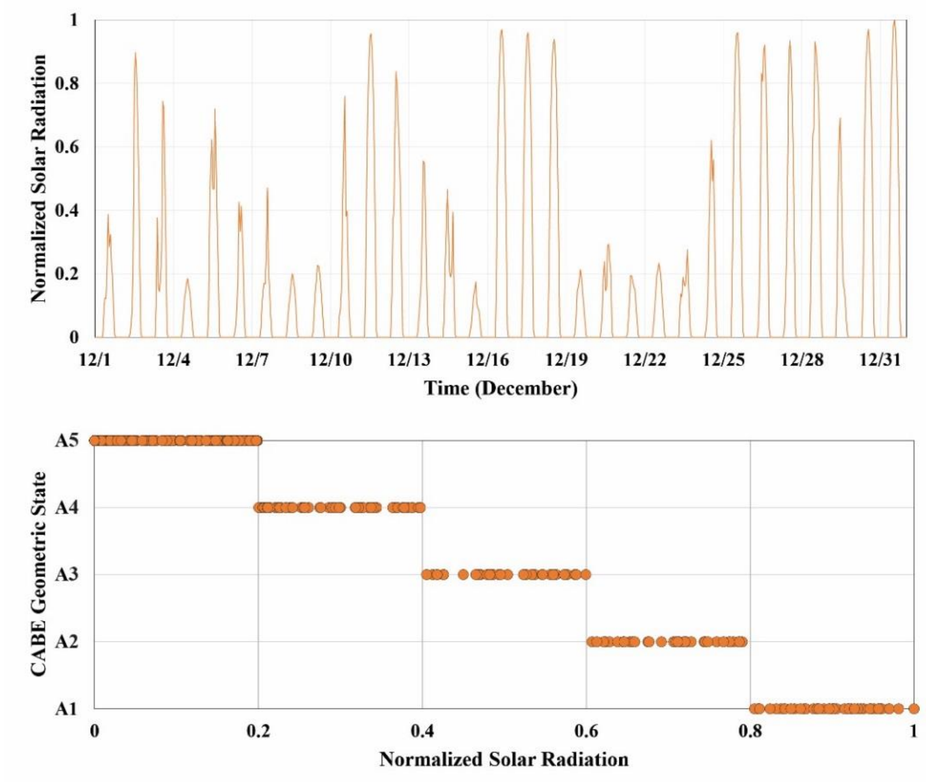


Figure 25. Relationship between the normalized solar radiation values and CABE geometric states in winter (December).

4.4.2. Results

CABE Model 2 was selected for Test case 2 because its patterns of geometric transformation could efficiently control the impact of CABE on incoming beam and diffuse radiation. Two independent simulation periods were set – July and December – to represent the summer and winter season. The same scenario shown in Figures 24 and 25 was used as the CABE behavior scenario in the MSSB method. In other words, BPS models with static shading scenarios (A1 to A5 in Figure 21) were created independently; then, indoor air temperature values were chronologically selected for each hour, based on the scenario in Figures 24 and 25.

The correlation trends between the indoor air temperatures measured using the PBM and the MSSB are shown in Figure 26. The temperature values in July ranged from 27.7°C to 36.8°C with a high R^2 value ($R^2 = 0.99$). The scatter plots for December ranged from 6.7°C to 36.4°C, with a relatively low R^2 value ($R^2 = 0.95$); since the indoor temperatures increased in December, these plots clearly indicate that there is a difference in calculating thermal conditions with the PBM, as opposed to the MSSB.

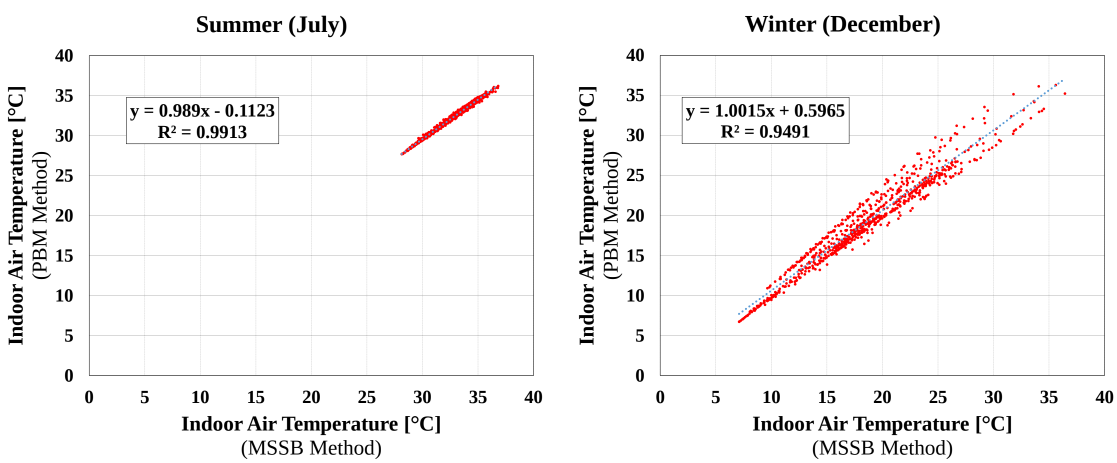


Figure 26. Correlations among the indoor air temperatures measured using the PBM and the MSSB in July and December (CABE Model 2).

To interpret the differences, the indoor air temperature profiles were compared to the outdoor air temperature, global horizontal irradiation (GHI), and solar radiation reaching the window without shading on three separate days: the 17th of July, and 15th and 31st of December. These dates were determined based on the GHI value, which is the sum of the direct and diffused radiation levels measured from a horizontal surface. The meteorological data indicated that the highest value of the daily average GHI was 308.6 W/m^2 on the 17th of July, and 165.4 W/m^2 on the 31st of December; the lowest GHI was 56.6 W/m^2 on the 15th of December.

Indoor air temperature profiles for each date were plotted with other related values (see Figures 27, 28, and 29). The temperature profiles gathered from the PBM and the MSSB were very close on the 17th of July; there were significant differences in GHI and incoming solar radiation reaching the window, due to the high altitude of the sun in summer (see Figures 27). Furthermore, the CABE behavior employed in the summer was close to this state when the incoming solar radiation increased. A small amount of incoming solar radiation did not influence the indoor temperature profile. Thus, both PBM and MSSB could be used for CABE performance evaluations when limited solar radiation reaches the window's surface.

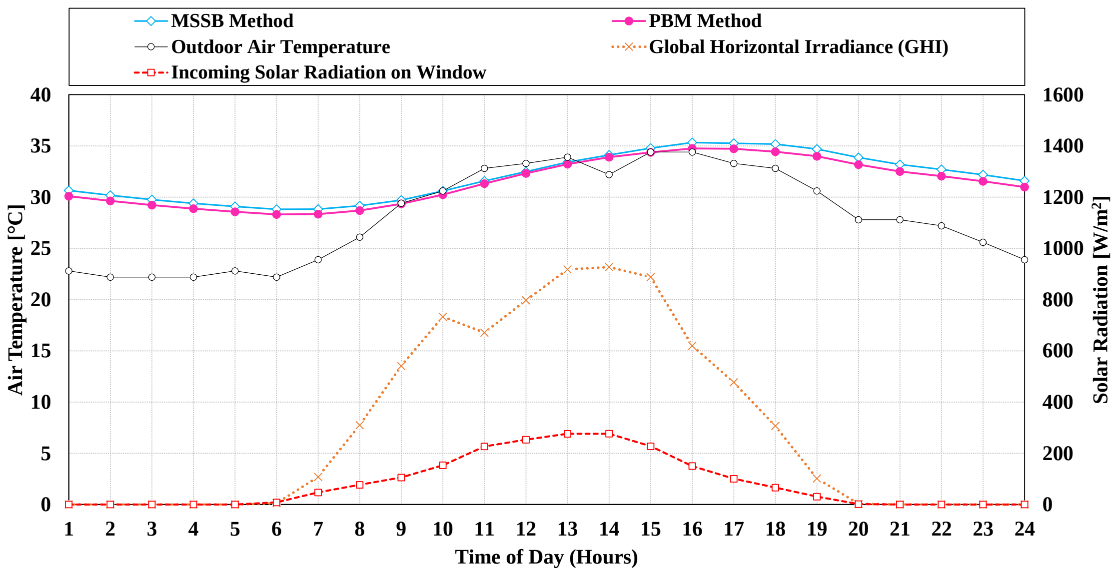


Figure 27. Indoor air temperature profile for the 17th of July.

Unlike the temperature profiles in July, significant differences were found for the 31st of December. Between 1:00am and 8:00am, and 4:00pm and 12:00pm, the PBM method produced higher indoor temperatures than did the MSSB method; the highest indoor temperatures from the PBM and the MSSB were 32.4°C at 4:00pm and 33.3°C at 3:00pm, respectively (see Figure 28). The patterns of indoor temperatures from the MSSB method and outdoor air temperatures were similar, especially when the temperature fell after 3:00pm. Conversely, the temperature profiles from the PBM method gradually fell after 4:00pm in comparison to the MSSB process. The delay in the decrease in temperature with the PBM originated from the time-lag effect of transient heat transfer and energy storage that could be documented when using a single simulation instead of multiple simulations added together. MSSB method could not provide feedback on the effects of the outcome selection process, due to the use of multiple independent simulations; this is a limitation of the MSSB method, as has been described in Chapter 2. Thus, until midnight, the time-lag effect was responsible for the differences in temperature profiles; these differences continued through the beginning of the next day.

The differences in temperature profiles occurred only on the 31st of December, which was when the incoming solar radiation on the window was higher than the GHI value (see Figure 28). The low altitude of the sun increased the amount of solar radiation reaching the window, which directly impacted the indoor air temperature profiles. Although the sun's altitude was low on the 15th of December, there was a small amount of solar radiation reaching the window due to weather conditions; the temperature profiles for both methods were similar (see Figure 29). Thus, the MSSB method increased errors in the CABE's performance when the angle of incidence was close to zero in sunny skies, regardless of the building's orientation. This was the reason why a squared correlation in December was less than the same in summer, especially when the indoor temperature increased, as shown in Figure 26. The PBM, then, will produce more reliable results regarding CABE performance and can be used regardless of building form, orientation, or sky conditions.

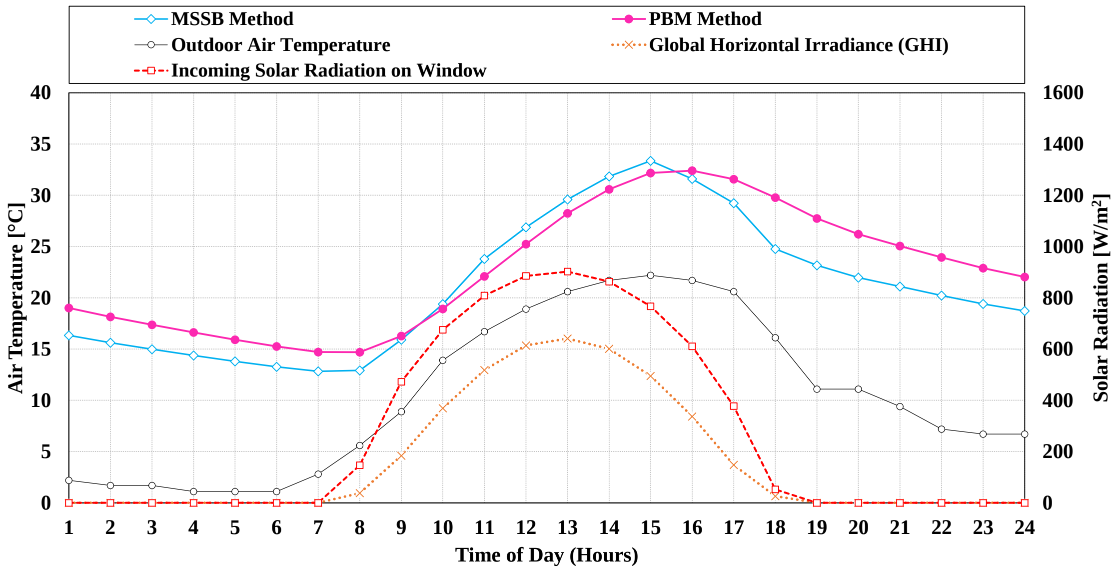


Figure 28. Indoor air temperature profile for the 31st of December.

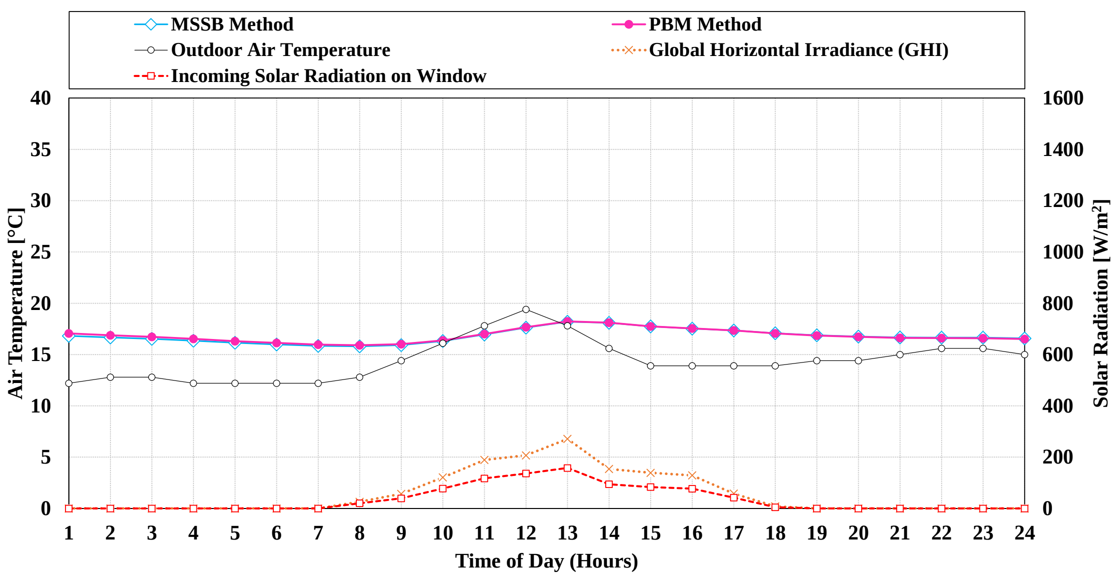


Figure 29. Indoor air temperature profile for the 15th of December.

4.5. Summary

This chapter delivered two test cases to validate the PBM method for use in evaluating CABE performance. The amount of solar radiation transmitted by CABE systems was compared to static shading conditions, with the assumption that the CABE's behavior only included the same scenarios as those with static shading. Although only a limited number of CABE behavior scenarios was considered, the results indicate that the PBM method can be applied to simulate CABE performance. To increase the reliability and robustness of the method, indoor air temperature profiles were simulated using a dynamic CABE behavior scenario that was generated based on the amount of incoming solar radiation on the window; the results were compared to those obtained from the MSSB method, the process traditionally used in CABE performance simulations. The temperature profiles indicated that the PBM method was able to include the energy storage effect for calculating heating and cooling loads, which cannot be presented when the MSSB method is used. This was especially clear when a large amount of solar radiation reached the window and one can assume that the energy storage effect was high.

In summary, the contributions of the PBM method to CABE performance evaluation can be summarized as follows:

- The method delivers more reliable evaluation results that include the effects of transient heat transfer and energy storage effects.
- CABE performance evaluation can easily be integrated into the design process by using a single BPS model. When the MSSB method is used, multiple BPS

models and data sorting process are required, depending on the number of CABE scenarios.

- Unlike the MSSB method, errors in simulation outcomes are not sensitive to the amount of solar radiation reaching the window. This means that the method can universally be applied to simulate CABE performance, regardless of the building's orientation, form, simulation period, and sky conditions.

In this study, reflectances among surfaces of the CABE and the interior of the building were not considered in the CABE performance simulations. A sensitivity analysis could be conducted to further investigate the impact of a CABE's reflectance on energy and daylighting performance.

The next chapter presents an optimization framework for CABE performance with linear and non-linear behavior patterns, in order to support the decision-making process.

CHAPTER V

AN OPTIMIZATION FRAMEWORK FOR CABE DESIGN DECISIONS

5.1. Overview

This chapter presents a multi-objective optimization framework to support the CABE design decision process. Unlike static shading, CABE systems include behaviors that significantly affect their performance; thus, well-informed strategies for scheduling behavior should be integrated to analyze a CABE's performance. To this extent, the goal of the CABE optimization framework was to produce a set of Pareto-optimal solutions with regards to the HBOO scenarios of a CABE option to provide an optimum CABE performance that considers both energy and daylighting. In this chapter, two conflicting objectives were addressed: to minimize cooling load and maximize daylighting performance ($sDA_{300/50\%}$) during the summer season in a hot and humid climate (Houston). The variables in the CABE performance optimization process were defined as having either a parametric linear or non-linear relationship to the degree of openness of the CABE design and certain environmental factors. The FBCS was used by integrating a parametric non-linear function; the goal was to efficiently conduct the optimization process in a large search space. The outcomes of this optimization study will inform designers of Pareto-front solutions that include cooling load and daylighting performance in their HBOO scenarios.

Section 5.2 Description of the Multi-Objective Optimization Study describes the objective functions, variables, and constraints used in the CABE optimization framework. *Section 5.3 Multi-Objective Optimization Framework for a CABE System* presents two test cases for the optimization framework. *Section 5.4 Summary* summarizes the optimization framework, discusses this study's limitations, and describes future research.

5.2. Description of the Multi-Objective Optimization Study

5.2.1. Objective Functions

In the previous chapter, all internal loads and their schedules in the BPS model were eliminated to minimize any possible interference from other components when validating the PBM method. The BPS model used in this chapter included all input parameters for loads and operation schedules, as described in *Section 3.3.2 Reference Building Model*. The simulation location was Houston, Texas, a hot and humid (2A) climate. The simulation period was one month in summer (July). The goal was to investigate the efficacy of the CABE system with optimum HBOO scenarios.

Two conflicting objective functions were employed to determine the optimal trade-off solutions: minimizing the cooling load and maximizing the daylighting performance. In terms of the daylighting performance index, sDA was integrated with the CABE control strategy. Although LEED offers credits related to daylighting performance when $sDA_{300/50\%}$ meets at least 55 percent of the floor area, in this study, the objective was to achieve the maximum percentage of $sDA_{300/50\%}$ without limits, which could have a completely opposite effect on the cooling load; a high percentage of sDA in the summer tends to increases cooling load. The hope was that the multi-objective optimization framework for the CABE system could achieve a set of solutions that would strike a balance between these conflicting objectives. The objective functions can be expressed as the following equations:

$$min \begin{cases} f_{\text{energy}}(x) \\ f_{\text{daylighting}}(x) \end{cases} \tag{2}$$

$$f_{\text{energy}}(x) = Q_{\text{cooling}}(x) \tag{3}$$

$$f_{\text{daylighting}}(x) = 100 - sDA_{300/50\%}(x) \tag{4}$$

where:

$f_{energy}(x)$ = the cooling load;

$f_{daylighting}(x)$ = the unsatisfied $sDA_{300/50\%}$; and

x = the HBOO scenario.

The minimum value for the unsatisfied $sDA_{300/50\%}$ was used as the objective function for daylighting to achieve the maximum $sDA_{300/50\%}$ value.

5.2.2. Variables and Constraints

A CABE's behavior is an important parameter for determining its performance; it can be represented as the degree of openness regardless of the CABE's transformation patterns. The PBM method allows for CABE HBOO scenarios to be parametrically updated to analyze the CABE's performance. In this chapter, The FBCS was implemented to efficiently control the HBOO scenarios in the PBM method, as described in *Section 3.2.3 Optimum CABE Scenario*. The main purpose of the FBCS was to manipulate the values for the environmental factors by integrating numerical models; the manipulated values were able to define various HBOO scenarios without changing the category in the PBM method. For example, Figure 30 describes the various relationships among the normalized solar radiation values reached on a southern-oriented window in Houston during the summer (July) and the CABE's geometric states; the degree of openness of ten geometric CABE states (A1 to A10) were then defined using a set of the normalized solar radiation values (see Figure 30A). The set of the normalized solar radiation values could be manipulated using parametric linear functions to define various HBOO scenarios without changing the category in the PBM method (see Figures 30B, 30C, and 30D). In the same way, parametric non-linear functions could be used to manipulate the set of normalized solar radiation values; this increased the number of HBOO scenarios and ensured a large search space for the optimization process (see Figure 31). Thus, various HBOO scenarios could be defined by changing a few variables in the parametric functions, instead of changing a portion of the category.

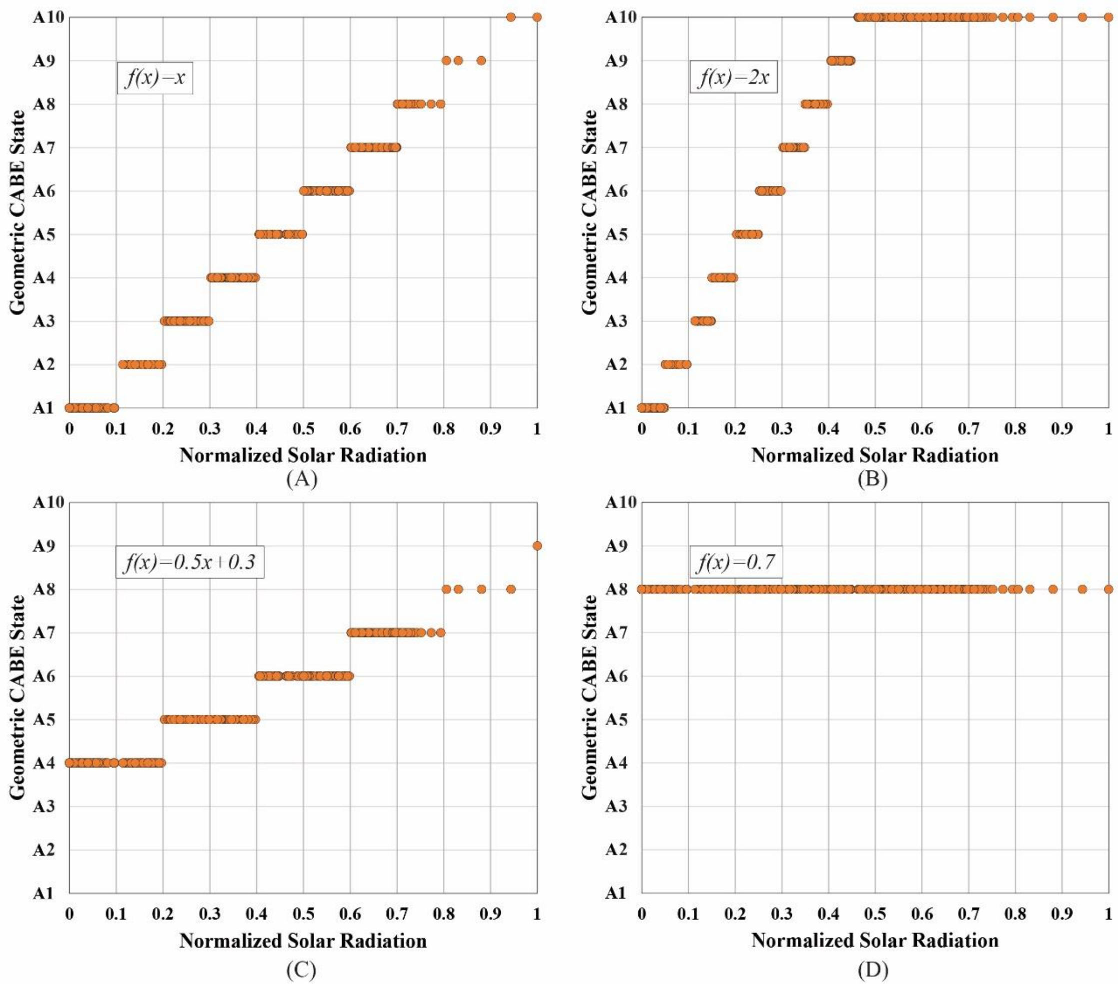


Figure 30. Examples of the FBCS with linear functions.

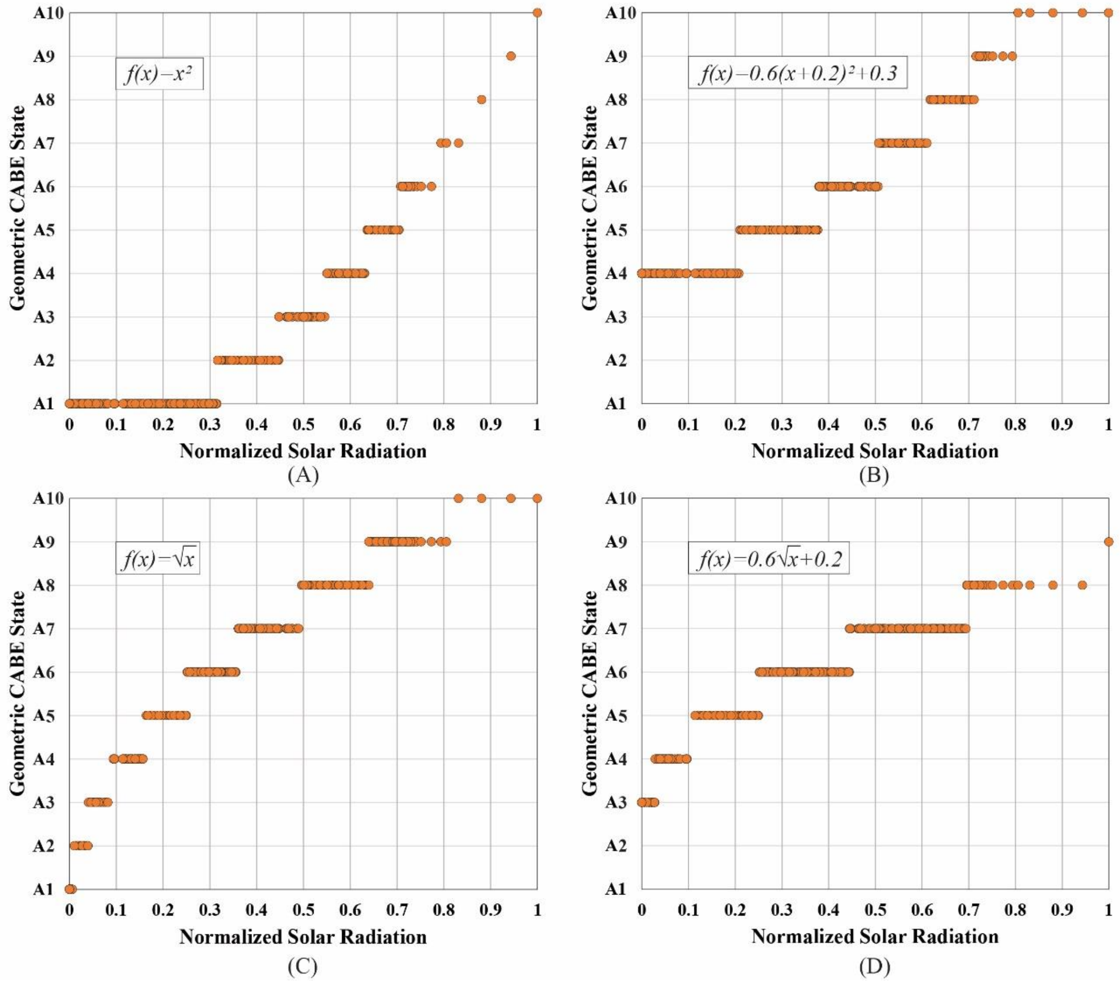


Figure 31. Examples of the FBCS with non-linear functions.

The parametric HBOO scenarios for the CABE design could be mapped on a BPS model using the PBM method; these parametric HBOO scenarios could then be generated using a parametric non-linear function with three variables, as follows:

$$f(x) = ax^b + c \tag{5}$$

where:

$f(x)$ = a set of manipulated solar radiation values;

x = a set of normalized solar radiation values from the original data sources;

a = variable 1 ($0 \leq a \leq 4$);

b = variable 2 ($0 \leq a \leq 4$); and

c = variable 3 ($0 \leq a \leq 1$).

The domain of the three variables was defined to represent various linear and non-linear functions to cover a large space, and served as a constraint to minimize the number of variables in the optimization process.

5.2.3. Multi-Objective Optimization Algorithm

In this research, an EMO method was implemented to find a set of Pareto-optimal solutions to the MOOPs. Octopus, a plug-in for EMO algorithms in the visual programing environment for Rhino, was used to accomplish this goal. The core algorithm was SPEA-2, which was developed by Zitzler et al. (2001); this algorithm is an improved elitist multi-objective evolutionary rule that performs better than others, such as SPEA (Zitzler and Thiele, 1999), PESA (Corne et al., 2000), and NSGA-II (Deb et al., 2000). Table 9 shows the list of values in the optimization algorithm that were used to solve the MOOPs addressed in this chapter.

Table 9. List of Values for the Optimization Algorithm Addressed in this Chapter

Parameters	Values
population size	50
maximum generations	20
elitism	0.5
mutation probability	0.1
mutation rate	0.5
crossover rate	0.8

5.3. Multi-Objective Optimization Framework for the CABE system

Two CABE models were used to conduct multi-objective optimization tests using the PBM; each model represented two-dimensional and three-dimensional geometric transformations in the CABE system. The following sections offer detailed descriptions of each model and their optimization results.

5.3.1. Two-dimensional CABE System (Test Case 3)

5.3.1.1. Description of the CABE Model

For the two-dimensional CABE system, CABE Model 2, with ten geometric states (A1 to A10), was used; its geometric configurations are presented in Figure 32. Although the geometric transformation patterns were the same for CABE Model 2, the use of more geometric CABE states made it possible to represent the smoother movement of the CABE system and produce more reliable results.

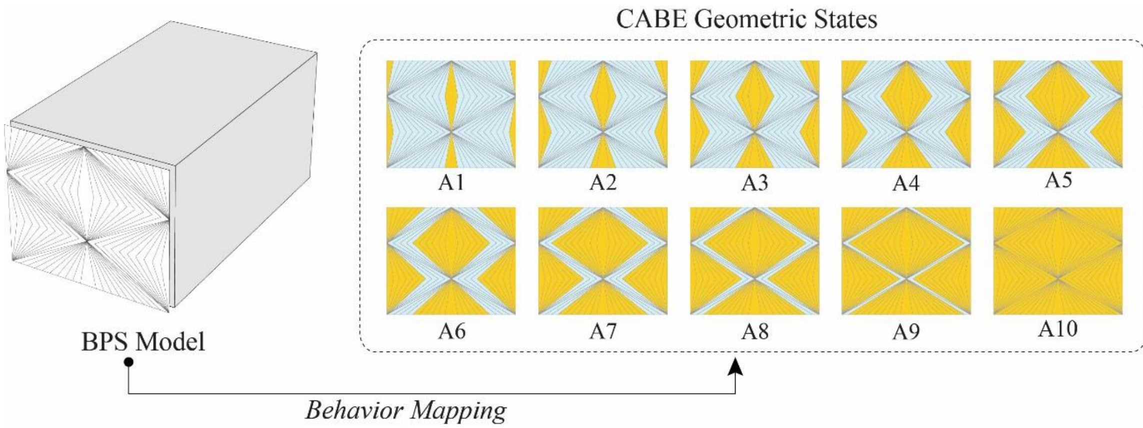


Figure 32. Geometric configurations of the CABE model used in Test case 3.

5.3.1.2. Results of the Multi-Objective Optimization

The MOO was conducted using a powerful commodity computer, running Windows 10 operating system (Quad-Core 4.0 GHz processors, 64G RAM). Each simulation in the BPS model in Test case 3 took 250 seconds; in total, the process took three days to produce 20 generations of simulations in Octopus. Each generation contained 50 individuals. Figure 33 presents the Pareto-frontier solutions for the MOO after 20 generations; each solution could have been selected as a final design option, each with a different emphasis. For example, Solutions (A) and (C) focused on reducing the cooling load (672 kWh of cooling load and 26.7% of sDA) and maximizing the daylighting conditions (700.79 kWh of cooling load and 66.7% of sDA), respectively; Solution (B) represented one of the best trade-off solutions considering both cooling load and daylighting conditions (679.70 kWh of cooling load and 46.7% of sDA) (see Figure 33).

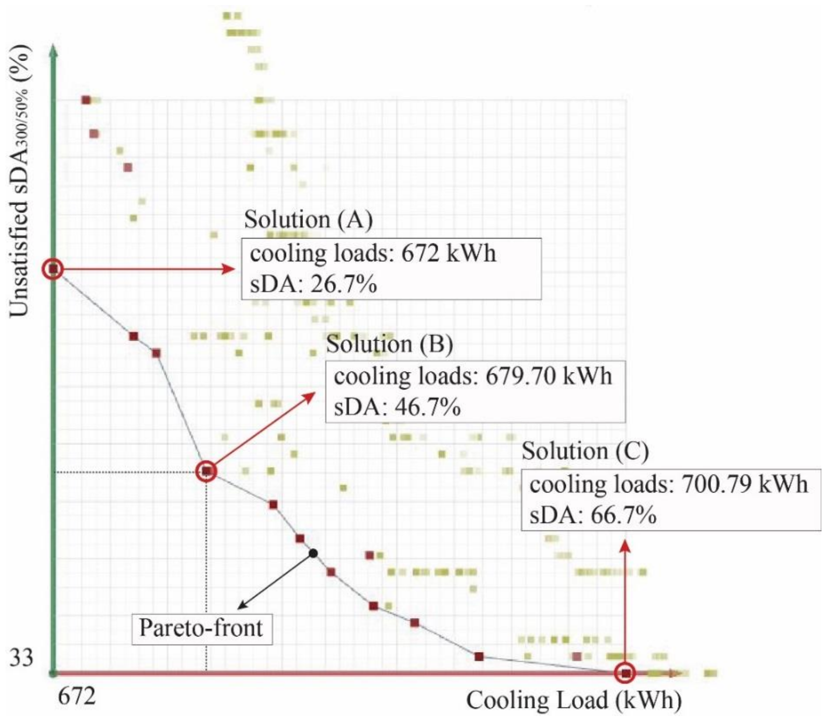


Figure 33. Pareto-frontier solutions for the MOO after 20 generations (Test case 3).

The variables for the MOO described in this chapter were the HBOO of the CABE system, represented as the three values in the parametric non-linear function; each solution contained a specific function to represent the relationship between the normalized solar radiation values and the CABE's geometric state. The three values in Solution (B) were: (a) 0.6, (b) 0.1, and (c) 0 in Equation (5). The relationship is expressed by the following Equation (6) and presented in Figure 34:

$$f(x) = 0.6x^{0.1} \tag{6}$$

where:

$f(x)$ = a set of manipulated solar radiation values; and

x = a set of normalized solar radiation values from the original data sources.

As shown in Figure 34, the geometric CABE state in Solution (B) was set as A6 for most of the range of normalized solar radiation values; small changes in the geometric CABE state occurred for the rest of the range of normalized solar radiation values (the A4, A5, and A7 states). This means that static shading (the A6 state) was effective most of time in July in Houston (a hot and humid climate) when considering both the cooling load and daylighting conditions.

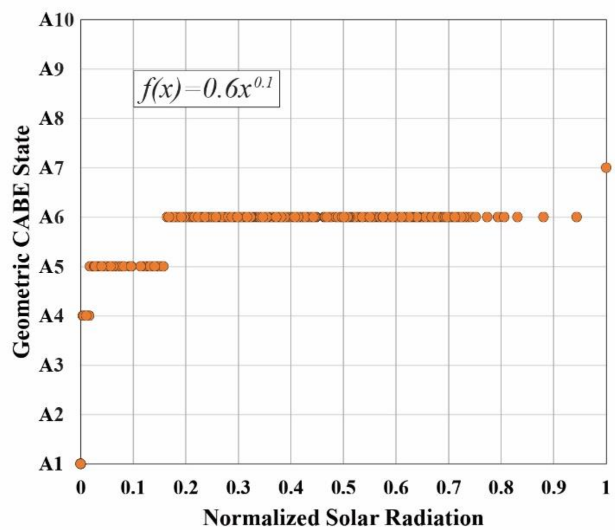


Figure 34. Relationship between the normalized solar radiation values (July) and the geometric CABE state for Solution (B).

To clearly represent the HBOO scenario for Solution (B) in Figure 33, the geometric CABE states in July were plotted based on time. The A6 state was in place for most of the day in July, in order to achieve Solution (B); small state changes occurred during the daytime, and the CABE system was fully open at night (see Figure 35). Figure 36 represents the relationship between the geometric CABE states and the amount of solar radiation reaching the window for July 17; the daily average GHI was highest on that day. During the nighttime, the solar radiation value was zero so the CABE state was fully open (state A1). Even though the solar radiation values increased during the day, states A5 and A6 were kept in position (see Figure 36). This resulted in the performance outcomes being similar to the results obtained from static shading (the A6 state); thus, it was concluded that CABE Model 2 was not particularly effective as compared with a static shading scenario, especially on southern-oriented vertical window surfaces in Houston (a hot and humid climate).

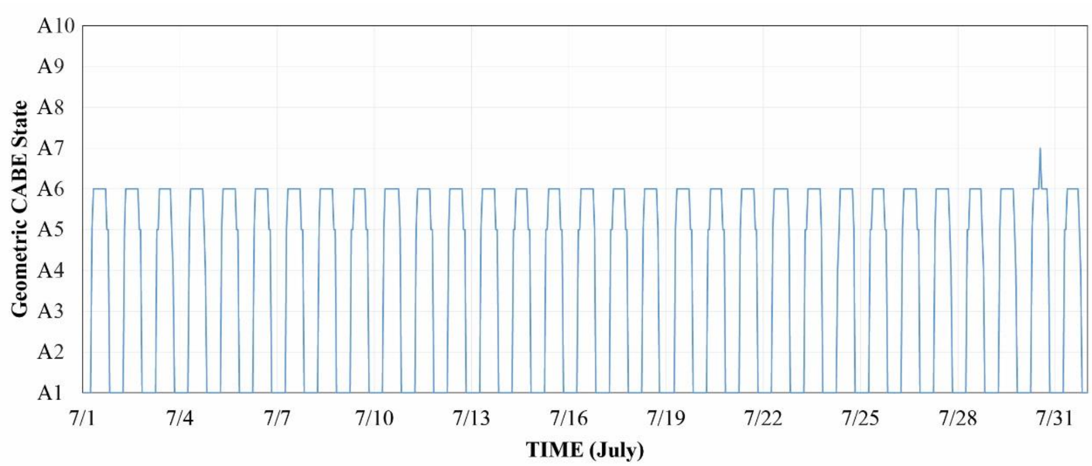


Figure 35. An HBOO scenario for July, based on the results of Solution (B).

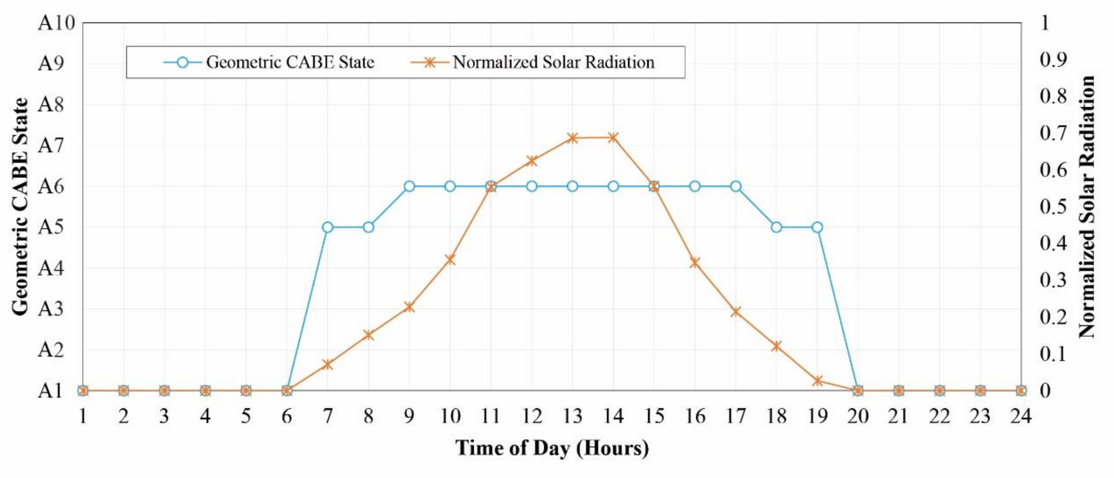


Figure 36. An HBOO scenario for the 17th of July, based on the results of Solution (B).

5.3.2. Three-Dimensional CABE System (Test Case 4)

A three-dimensional CABE system was developed for Test case 4; it represented the complex CABE installed in the Al Bahr towers in Abu Dhabi (Oborn, 2012). Its geometric configuration consisted of five states (A1 to A5) (see Figure 37). Although the actual geometric transformations of the CABE in the Al Bahr towers were created based on folding motions, the CABE model used in this section was developed based on a sliding motion to minimize computational cost. For the same reason, five geometric states were used; however, using more geometric states would have produced more reliable outcomes.

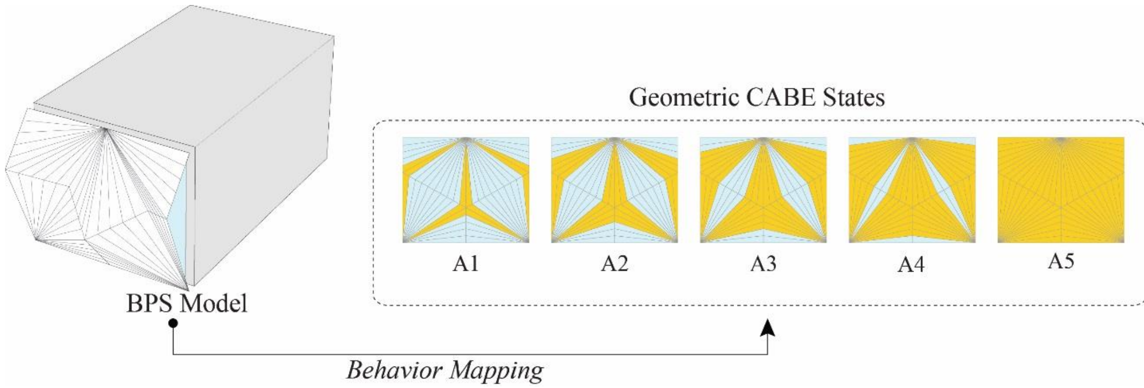


Figure 37. Geometric configurations of the CABE model used in Test case 4.

5.3.2.1. Results of the Multi-Objective Optimization

The MOO was performed using the same computer system employed in Test case 3. Each simulation took 308 seconds; the production of 20 generations in Octopus took four days. Each generation contained 50 individuals. The Pareto-front solutions formed after these 20 generations are presented in Figure 38. Each solution represented a design option with a particular performance emphasis. Solutions (A) and (C) stressed reducing the cooling load (587.48 kWh of cooling load and 16.7% of sDA) and maximizing the daylighting conditions (689.70 kWh of cooling load and 75% of sDA), respectively; Solution (B) represented one of the best trade-off solutions, considering both cooling load and daylighting conditions (624.68 kWh of cooling load and 46.7% of sDA) (see Figure 38).

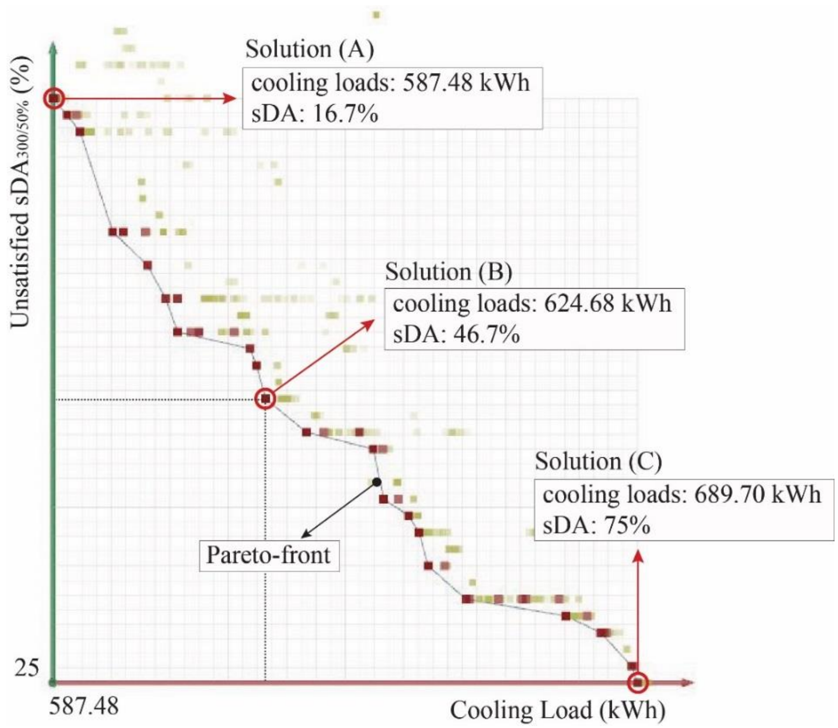


Figure 38. Pareto-frontier solutions for the MOO after 20 generations (Test case 4).

As with Test case 3, various HBOO scenarios for the CABE system were generated using three variables in a parametric non-linear function; the outcome of Solution (B) was obtained based on the relationship between the normalized solar radiation values and the CABE's geometric state, as presented in Figure 39. The three values for Solution (B) were: (a) 0.8, (b) 0.5, and (c) 0.3 in Equation (5), and the relationship was written following Equation (7):

$$f(x) = 0.8x^{0.5} + 0.3 \tag{7}$$

where:

f(x) = a set of manipulated solar radiation values; and

x = a set of normalized solar radiation values from the original data sources.

Unlike the relationship in Test case 3 (see Figure 34), a range of geometric CABE states was assigned for normalized solar radiation (see Figure 39). This meant that the dynamic change in the geometric CABE state depended on the amount of solar radiation reaching the window's surface; the CABE system used here was effective in a hot and humid climate when more geometric states were considered.

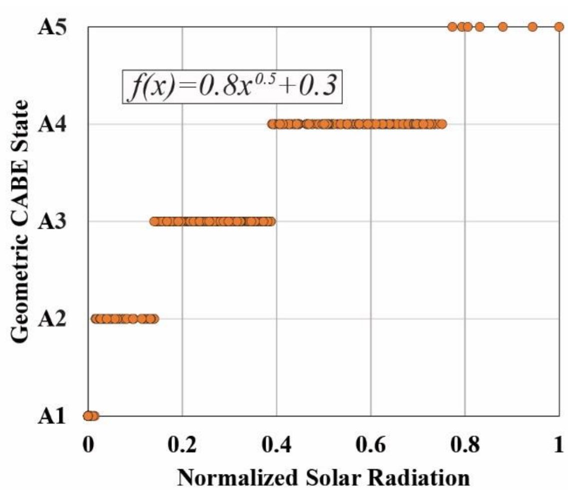


Figure 39. Relationship between the normalized solar radiation values (July) and the CABE's geometric state in Solution (B).

Base on the relationship shown in Figure 39, time-based geometric CABE states were plotted for July. All geometric CABE states were positioned during the daytime in July in order to achieve the cooling load and daylighting conditions seen in Solution (B) (see Figure 40). This trend was clearly described in the relationship between the geometric CABE states and the amount of solar radiation reaching the window for the 17th of July (see Figure 41). During the night, the solar radiation value was zero so the CABE state was fully open (the A1 state). When the solar radiation values increased during the daytime, the geometric CABE state changed accordingly, with a similar pattern of solar radiation values (see Figure 41). The conclusion was that CABE Model 3 would likely be more effective than the static shading scenario, especially with regards to southern-oriented vertical window surfaces in Houston (a hot and humid climate).

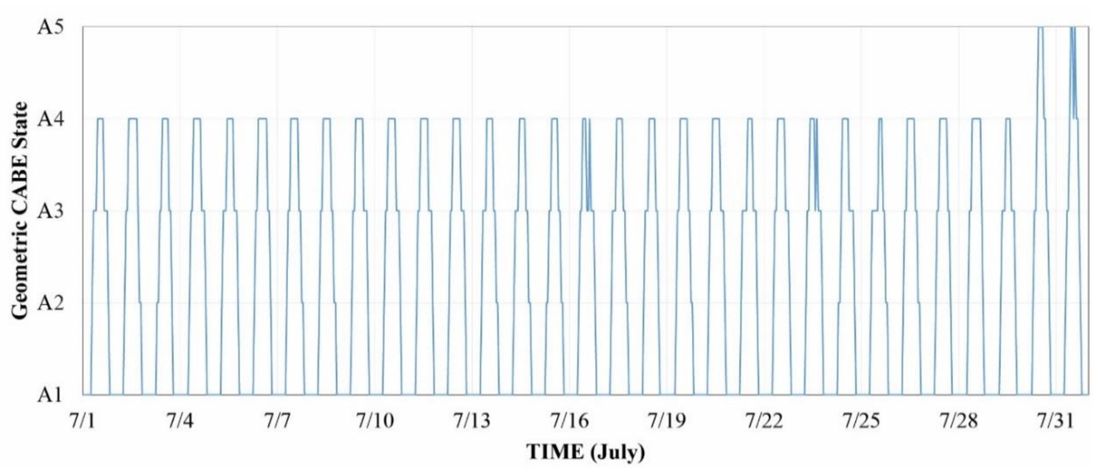


Figure 40. An HBOO scenario for July, based on the results of Solution (B).

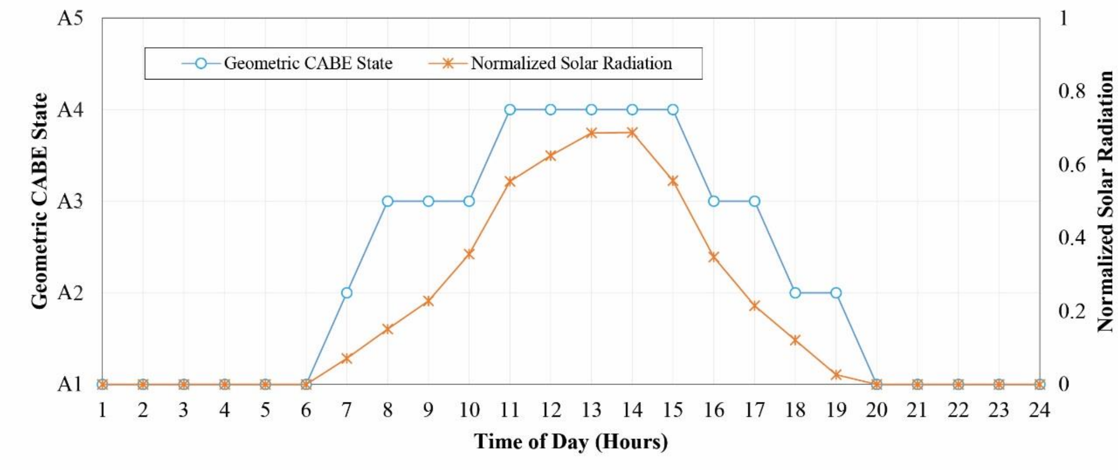


Figure 41. An HBOO scenario for the 17th of July, based on the results of Solution (B).

5.4. Summary

This chapter presented a multi-objective optimization framework to support CABE-related design decisions. The variables in the MOO were the HBOO scenarios in the BPS model of the CABE system. The objective functions were the minimization of the cooling load and maximization of the daylighting conditions via a CABE system during the summer season (July) in Houston (a hot and humid climate). The FBCS was implemented in the MOO process to efficiently control the variables; this was accomplished by integrating a parametric non-linear function that changed the relationship between the CABE's geometric state and the normalized solar radiation values in July. A set of optimum HBOO scenarios for two different CABE models (two- and three-dimensional transformation patterns) were achieved based on Pareto-front solutions to the objective functions. An evaluation of the Pareto-front showed that use of the MOO process could support CABE design decisions.

The contributions of multi-objective optimization with the CABE system can be summarized as follows:

- Parametric HBOO scenarios could be integrated with the BPS model to achieve the CABE's optimum performance in HBOO scenarios, considering conflicting objectives.
- The use of the FBCS could efficiently present and control the HBOO scenarios in the optimization process.

It is important to note the limitations of this optimization framework and discuss future research:

- In this study, monthly solar radiation values reaching the window were used to generate HBOO scenarios for the CABE system; the domain of the normalized solar radiation values included the highest and lowest levels during working hours over the entire time span considered. Ideally, the domain of the normalized solar radiation values should be determined by the daily interval of the highest and lowest solar radiation levels each day, in order to dynamically respond to environmental changes; this approach will produce more reliable results, and will be pursued in future research.
- The simulation period and location of the optimization framework were one month in July in Houston (a hot and humid climate). A more long-term simulation period such as a season or year will produce better outcomes; testing

in different climate zones and with various orientations will further facilitate the implementation of CABE systems.

- In terms of energy consumption, this research only included the cooling load. Other energy demands such as electric light energy should be incorporated to investigate the impact of the CABE system on daylighting performance and energy consumption.

CHAPTER VI

SUMMARY

6.1. Overview

This research produced the foundation for a performance-driven CABE design method that is a contribution to the field of CAD research on the topics of parametric modeling, performance-driven design, and multi-criteria optimization. This chapter summarizes the development of this new CABE performance evaluation method and compiles the evidence for these contributions. Also, future research related to performance-integrated CABE design is discussed.

6.2. An Algorithm for CABE Performance Evaluation

Unlike static shading, the main characteristic of a CABE system is the inclusion of time-series behavior scenarios that allow the mechanism to respond to various environmental factors. This innovative aspect, however, often results in making performance evaluations of complex CABE alternatives extremely difficult and sometimes inaccurate. A direct consequence of this imitation in evaluation methods is a lack of integration of performance into the CABE design method. An effective method for designing a CABE must address the following steps: 1) define a suitable CABE behavior associated with various environmental factors of interest, 2) represent the CABE's time-series behavior within a Building Performance Simulation (BPS) model, and 3) manage the CABE's behavior information and performance for use in design decisions.

To overcome these challenges, a new algorithm for evaluating CABE performance called PBM was developed by integrating parametric modeling, performance simulations, and multi-criteria optimization; the process followed three steps: 1) development of the FBCS for the CABE's behavior control (Step 1: CABE Behavior Control); 2) generation of the HBOO scenarios for the CABE technology included in the BPS model (Step 2: CABE Behavior Generation); and 3) simulation of the CABE's performance with respect to building performance factors (Step 3: Scheduled Behavior Simulation). The PBM was integrated via an EMO technique; it addressed two conflicting objectives by generating a set of Pareto front solutions (Step 4: CABE Performance Optimization). The following sections summarize the contributions of each step.

6.2.1. CABE Behavior Control

In this research, a CABE behavior control system called FBCS was developed to produce various HBOO scenarios by integrating a set of values related to environmental (weather) factors. This work contributes to the field of CABE performance evaluation and optimization by providing a means of efficiently controlling HBOO variables for use in alternative schemes. In general, when the EMO technique is implemented, a large number of variables can result in failure of the optimization process or inaccurate results. In this research, CABE behavior was generated using a discrete model of the environmental factors. The number of distinct categories needed to be increased when attempting to achieve more sensitive CABE behavior. Thus, the goals of the FBCS were to: 1) reduce the number of variables and efficiently control the CABE's HBOO elements, regardless of the number of geometric CABE states or categories of environmental factors; and 2) conduct the optimization process without errors or failure. The test cases show that the FBCS can efficiently produce various HBOO scenarios, based on the selection of functions. Multiple functions can also be used to represent discontinuous HBOO scenarios.

6.2.2. CABE Behavior Generation

The development of a process for representing CABE behavior in a single BPS contributes to the field of CABE performance evaluation by generating HBOO schedules for CABE operation. Relationships among the various geometric CABE states and values of the environmental factors on a surface can be created by matching them to a discrete model; this relationship assist in representing the HBOO scenarios for the CABE performance simulation. Previous studies have addressed HBOO scenarios based on a single threshold of environmental factors expressed as a binary CABE state (open or closed), or multiple thresholds of environmental factors as multiple CABE states (gradually moving from open to closed) via a linear regression. This representation accounts for a limited number of HBOO scenarios, resulting in the loss of superior design alternatives. On the other hand, by following this process, a substantial number of HBOO scenarios can be generated and used in current BPS tools as CABE operation schedules. In this research, hourly solar radiation values were used as an environmental factor and converted into discrete categories. The geometric CABE states at each hour were defined based on the hourly solar radiation values; the result was the production of HBOO scenarios that could be changed by using the FBCS. In other words, each CABE state included an operation schedule for responding to changes in the environment; the schedule was then linked to a BPS model of a CABE system, as discussed in the next section.

6.2.3. Scheduled Behavior Simulation

The performance of a CABE system can be simulated by using a single BPS model that includes all of the CABE's geometric states and their operation schedule (generated from the previous step). This contributes to the performance-driven CABE design process by producing more reliable simulation outcomes. The main challenge for using a BPS in evaluating CABE performance is that because of the need for data entry to set design values in the previous methods, only a few CABE alternatives and HBOO scenarios can be simulated in a realistic design process. Also, complex 3D CABE geometry cannot be simulated, due to limitations in the current simulation tools and previous modeling methods. Existing CABE performance evaluation method use multiple simulations with static shading (MSSB method). In other words, the evaluation of a CABE's performance are the sum of simulation results for each hour, obtained from independent simulations of static shading scenarios; the optimum CABE performance is determined by selecting the best outcomes for each hour from these independent simulations. Although this method is useful for CABE performance evaluations when considering coarse CABE behaviors such as setting the CABE operation to adjust seasonally, in terms of short-term daily CABE operation, the MSSB approach cannot account for thermal performance effects that may vary hourly or daily, such as the time-lag effect in thermal performance simulations or uncertainty issues in human behavior and weather conditions. This is problematic, because the results of thermal load calculations at specific time steps provide important feedback for the load calculations of subsequent time steps. In the PBM method, a single BPS model includes all geometric CABE states; each is controlled using a parametric operation schedule generated from the previous step. Ultimately, the BPS for a CABE can include the time-lag effect and produce more reliable results in terms of CABE performance.

6.2.4. CABE Performance Optimization

In this research, the integration of PBM and EMO was shown to present a multi-criteria optimization framework to support the CABE design decision process. The goal was to identify HBOO scenarios for a CABE system that produce optimum performances. Two conflicting objectives for the design were to minimize the cooling loads and maximize the daylighting performance; the variables were the HBOO scenarios for the CABE's operation that could be generated using parametric FBCS. Multi-criteria optimization was conducted for two different CABE models. The outcomes showed that the optimization framework could successfully inform designers of a CABE's optimum performance by producing optimal HBOO scenario. Ultimately, this process can be used to make better design decisions related to performance-driven CABE designs

6.2.5. Summary of Contributions

The contributions of this research touch upon three different fields within CAD research: parametric modeling, building performance simulation, and multi-criteria optimization.

(1) The use of parametric modeling technology supports the development of the PBM for generating various CABE operation schedules used in a single BPS model by defining the relationship between environmental factors and their thresholds.

(2) As compared to the MSSB approach, the PBM for CABE produces more reliable results in terms of the CABE's thermal performance. It can be implemented to simulate any CABE alternative, regardless of the building's orientation, form, simulation period, or sky condition.

(3) The use of the FBCS successfully supports a multi-criteria optimization framework for CABE-related design decisions; it can also efficiently control a large number of HBOO scenarios using only a few variables, regardless of the number of geometric CABE states.

These three contributions provide information to support designers making better CABE-related decisions by integrating both parametric modeling and performance simulation tools into the design process.

6.3. Future Research

This research established a foundation for evaluating CABE performance and optimizing the related HBOO scenarios. Further work contributing to performance-driven CABE research can be divided into three categories:

- Generations of CABE behavior:

(1) This research generated HBOO scenarios based on the values of the environmental factor of solar radiation. Inclusion of additional environmental factors (both external and occupant-oriented elements) is likely to generate different HBOO scenarios that might produce alternative schedules with higher performance.

(2) The integration of occupant behavior with real-time interactions with environmental factors will produce more realistic HBOO scenarios and optimum CABE performance.

- Performance Simulations for CABE systems:

(1) In addition to the minimization of the cooling loads and maximization of daylighting performance, other energy demands such as electric lighting could be included to produce more reliable results. Other simulations could address objectives such as glare, view of the outdoors, and natural ventilation. However, the framework for optimization via a Pareto-front could be employed to integrate performance simulation addressing additional criteria.

(2) In this research, it was assumed that no solar radiation was reflected from the CABE surfaces or the ground. Also, all CABE surfaces were assumed to have 100% opaqueness when the CABE states were activated. The impact of a CABE's material properties with respect to reflection, thermal conduction, and other factors could be investigated further and would likely deliver more accurate results.

(3) This research investigated the effectiveness of a CABE system in hot and humid climate conditions during the summer season (July). Testing of additional climate conditions and long-term analysis are required to further explore the effectiveness of CABE systems.

(4) The development of a standard of performance for CABE systems is necessary and can be accomplished by establishing valid performance indices; this will support CABE use at the conceptual design stage. The tools and methods produced in this research can play an important role in validating standards for CABE performance.

(5) Validation of the method could be achieved through empirical testing of the method produced by this research.

- Actuation of the CABE system:

(1) Research in advanced materials and CABE designs could rely upon well-informed CABE behavior scenarios obtained from the outcomes of this research.

(2) Installation and maintenance costs could be included in future work to facilitate better choices among CABE alternatives.

(3) Focus group testing in design studios and professional practice could be conducted to investigate the usability of the PBM method in the design and fabrication of CABE systems.

This research has filled a significant gap in design methods by defining a method that can guide designers to make better decisions about a CABE. As such, it provides a modest step toward achieving more energy efficient and better optimized designs and a more sustainable environment.

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